Automated Strategic Visualisations and User Confidence

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Abstract

Data visualisations aim at providing accessible and interpretable information for people. At a strategic level, such representations can be used to stimulate decision making. We have found that users are however hesitant to exploit unfamiliar visualisations, and require more material to be confident about their description of an unbiased representation of data.

In this thesis we aim at exploring which characteristics affect users' confidence in their ability to interpret and explain Topic Maps. These visualisations display the multi-dimensional thematic abstraction of large document collections, and as such require an automated generation process. In three qualitative studies, we challenge participants' confidence with stimuli and scenarios, and analyse their responses. The studies focus on: Explanation Systems, Topic Map layouts, and mapping processes.

In our studies, we demonstrate that the use of data-driven and interactive Explanation Systems gives users a sense of control, allowing for an enhanced interpretability and confidence. We then found that structure and narrative are both equally important characteristics of layouts for a confident presentation of Topic Maps. We finally explore mapping processes in detail, and establish that constructive mapping methods are more fit to improve user confidence than reductive ones.

This thesis, in summary, defines a comprehensive understanding of user confidence in automatically generated visualisations.

Résumé

La visualisation de données permet de rendre plus compréhensibles l'information au moyen de représentations graphiques. D'un point de vue stratégique, celles-ci peuvent être utilisées à des fins décisionnelles. Il est cependant apparu que l'un des principaux freins au recours à ces méthodes résidait dans la réticence des utilisateurs à exploiter des visualisations inhabituelles, par manque d'assurance pour décrire et justifier un processus de création non-biaisé.

Dans cette thèse, nous explorons les caractéristiques jouant sur la confiance des utilisateurs quant à leurs aptitudes à interpréter et à expliquer des Topic Maps. Ces visualisations présentent la classification thématique et multi-dimensionnelle de plusieurs milliers de documents, requérant ainsi un traitement automatique. Au cours de trois études qualitatives, nous interrogeons plusieurs participants soumis à des stimuli et à des scénarios testant leur confiance. Ces études portent sur: les systèmes d'explication, l'agencement de Topic Maps, et les algorithmes d'agencement.

Les résultats obtenus montrent que l'utilisation de systèmes d'explication interactifs et spécifiques aux données offre un meilleur contrôle aux utilisateurs et renforce leur compréhension et leur confiance. Nous découvrons ensuite que, dans les agencements de Topic Maps, structure et narration sont également déterminants pour une présentation confiante. Enfin, l'exploration détaillée des algorithmes d'agencement montre que les processus constructifs sont plus susceptibles de favoriser la confiance utilisateur, par rapport aux processus réductifs.

En résumé, cette thèse propose une compréhension des facteurs liés à la confiance utilisateur vis-à-vis des processus automatiques de création de visualisations.

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List of Terms

In the following list, we outline the terms used in this document and their associated definition in the context of this thesis.

Agglomerative Method

Layout Method specific to the agglomerative mapping process and the agglomerative Explanation System.

Explanation System

Visual, interactive, and data-driven mechanism representing a mapping process. This thesis uses two types of Explanation System, one for the projective mapping process and one for the agglomerative mapping process.

Layout mapping

Application using topic to topic distance information to create a position and clustering data for Topic Map.

Layout Method

Combination of both mapping process and Explanation System, as perceived by users.

Mapping process

Series of algorithms implemented within a layout mapping application to generate the placement of topics within a Topic Map. This thesis describes two types of process: projective and agglomerative.

Projective Method

Layout Method specific to the projective mapping process and the projective Explanation System.

Topic Map

Automatically generated data visualisation representing topics organised by similarity.

Topic Map layout

Set of perceptible features of a Topic Map, for example: the arrangement and position of topic cells, or the cluster information.

Topic modelling

Application uncovering and classifying latent themes, known as topics, within a collection of documents. It outputs a list of topics (weighted lists of words) and the topic to topic distance information based on their weights in the documents.

User

A person using Topic Maps. This thesis focuses on users with non or little technical knowledge, e.g. knowledge in mapping processes.

User confidence

The perception, of a user, of their own ability to carry out a task, e.g. interpreting and explaining Topic Maps.

List of Symbols

The following list presents the symbols and associated data structures used for the topic modelling and layout mapping processes.

Symbol	Definition
T	List of topics. Comprises of a) a topic identifier, b) a list of weighted labels (each label as a word and its weight in the topic), c) Cartesian coordinate data, and d) a cluster identifier.
c	Number of clusters in a Topic Map.
D	Topic dissimilarity matrix. $D_{t,t'}$ is the normalised dissimilarity measure between topics t and t' (0 is exact similarity, and 1 is complete dissimilarity).
	Topic Modelling
θ	Multinomial distribution of topics over documents. $\theta(t\|d)$ represents the probability of having the topic t in document d.
ϕ	Multinomial distribution of words over topics. $\phi(w\|t)$ represents the probability of having the word w in topic t.
α	Parameter of the Dirichlet prior on θ.
β	Parameter of the Dirichlet prior on ϕ.
υ	Topic assignment in a topic model generative process. $\upsilon(i,d)$ is the topic assigned to the i^{th} token in document d.
ω	Word assignment in a topic model generative process. $\omega(i,d)$ is the word assigned to the i^{th} token in document d.
υ_{count}	Count of topic assignment in documents. $\upsilon_{count}(t,d)$ is the number of token in document d assigned to topic t.
ω_{count}	Count of word assignment in topics. $\omega_{count}(w,t)$ is the number of token in topic t assigned with word w.

Symbol	Definition
L	List of lemmatised documents used to sample a topic model, describes ω.
Θ	List of per-document topic distributions. $\Theta_{d,t}$ is the weight of topic t in document d.
Φ	List of per-topic word distributions. $\Phi_{t,w}$ is the weight of word w in topic t.
U	List of per-topic relevant documents. U_t is the list of all relevant documents for topic t.
V	List of topic vectors in topic space. $V_{t,t'}$ is the normalised sum of topic t''s weights in the documents relevant to topic t.
	Projective Layout Mapping
Γ	Nearest-neighbour graph of topics based on D.
δ	Nearest-neighbour graph distance matrix. $\delta_{t,t'}$ is the shortest distance between topics t and t' in Γ.
τ	Matrix operator converting distances to inner products.
C	Centring matrix.
λ	Eigenvalues of $\tau(\delta)$, in decreasing order. λ_p is the p^{th} eigenvalue.
ν	Eigenvectors of $\tau(\delta)$, in decreasing order. $\nu_{p,t}$ is the t^{th} value of the p^{th} vector.
O	Multi-dimensional embedding of δ, and by extension of D. $O_{t,p}$ is the coordinate of topic t in dimension p.
P	Two-dimensional embedding of δ, and by extension of D. Subset of O.
B	Boundary box of G, estimated from the interquartile ranges of P.
f_s	Factor used to control the size of B, and of G by extension.
G	Hexagonal grid computed in the space as P, on which topics are mapped.
f_c	Factor used to control the number of cells in G, the more cells are introduce, the less dense a Topic Map will be.
s	Size of an hexagon in G.

Symbol	Definition
δ'	Euclidean distance matrix between topic points in P and grid cells in G.
ϵ	Euclidean distance between a topic point in P and its nearest mean in the K-means++ algorithm.
Agglomerative Layout Mapping	
ℓ	Linkage table of topics, representing the cluster hierarchy. ℓ_i is the i^{th} node in the table, and comprises of two child nodes and a distance measure at which the children merge.
ℓ_{root}	Root node of ℓ.
N	List of ℓ nodes describing clusters of topics.
${\eta^l}_A$	List of hexagons neighbours of a cluster of hexagons A at distance l. The neighbours can be direct ($l = 1$) or further ($l > 1$).
γ	Operator for the translation of a cluster of hexagons.
ρ	Operator for the rotation of a cluster of hexagons.
ι	Isle factor used to control the density of the agglomerative Topic Map layout.

Chapter 1

Introduction

1.1 Motivation

Topic modelling is an extremely popular method for summarising large document collections as sets of themes, or "topics" [32, 71, 79]. The results are often viewed in the form of a Topic Map [1] [1, 45, 87] in which the topics are automatically laid out by similarity. That is, the closer the topics are, the higher their similarity. An example is shown in Figure 1.1.

We have discussed the use of such maps to present the content of research outputs with research managers (one in a national organisation, and one group at institutional level). During these informal interviews, we have found that they find Topic Maps both engaging and informative. However, when they consider their use for potentially high impact activities, e.g. university research summarisation or strategy generation, they begin to question the methods by which Topic Maps are produced.

In particular, they feel the need to be able to explain these methods, in order to assure other stakeholders that the maps are an unbiased and true reflection of the data. However, they often lack the confidence to provide these explanations. We believe that this situation results in a low uptake of these visualisations.

[1] In this thesis, the term *Topic Map* exclusively refers to automatically generated visualisations of topic models.

The methods used for generating Topic Maps comprise two main types: those that are used to generate the topics, i.e. topic modelling, and those that are used to lay out the topics in a map, i.e. layout mapping. This thesis focuses on the latter, and addresses the users' confidence in their ability to interpret and explain its automation.

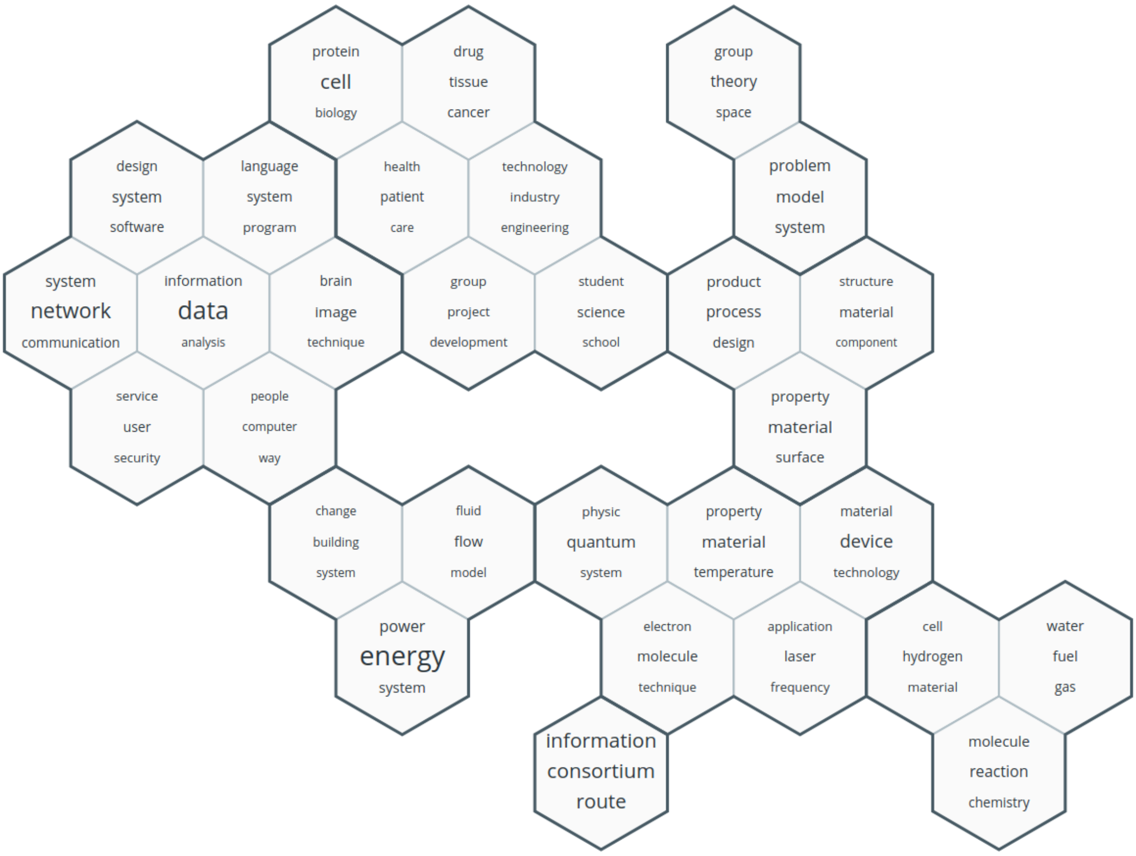

Figure 1.1: Example of a Topic Map visualising a research corpus. Each hexagonal cell in the grid represent one topic. Similar topics are positioned in proximity of each other and clusters of topics are indicated with bolder boundaries.

1.2 Research Goal and Objectives

Our research goal is to determine ways of increasing users' confidence in their ability to explain automated Topic Map layouts to themselves and third parties. This goal led us to divide it into three main research objectives.

We will first investigate the effects of data-driven Explanation Systems on the users' confidence in their ability to interpret Topic Maps for themselves, with the aim to present them to an audience. Such systems are designed to expose the reasoning trace of mapping processes using the user's data rather than generic examples.

We will then investigate the effects of Topic Map layouts' visual characteristics. That is, when presented with a Topic Map, which visual characteristics are prominent to the users, and how do they use them to better interpret and explain the Topic Map?

We will finally investigate the effects of mapping processes' process characteristics. That is, when exposed to a Topic Map's mapping process, how do users interpret the premises and details of the process, in relation to their Topic Map explanation task?

1.3 Methodology

To explore these objectives we conduct three sets of semi-structured scenario-based interviews. Early in our research, we have found that quantitative measures, such as duration or accuracy of tasks, or confidence ratings, do not allow participants to fully express the complex nuances they experience when asked about their confidence. Using a qualitative approach let us discuss with the participant the factors influencing their confidence and the impacts on their abilities to carry out tasks.

Qualitative methods however present limitations. Firstly, the findings drawn from these interviews cannot be statistically tested, and should therefore not be taken as universal results. Instead they provide cues to discuss design recommendations. Secondly, our results' quality primarily relies on the interpretation of participants' statements. As such we need guidelines to evaluate whether a statement does incorporate notions of confidence (positive or negative) or not. We ground these guidelines from the results of our first study (see Section 4.7) and use them in our two subsequent studies.

In order to effectively challenge and study the confidence of users, we focus our work on non-technical users, i.e. users with no or little knowledge of the mechanisms used to build Topic Maps. For each of the three studies conducted, we therefore recruited participants fitting this profile and new to our research.

1.4 Contributions

This thesis makes three main contributions with respect to the users' confidence concerning Topic Maps.

Firstly, we show that the use of data-driven interactive Explanation Systems improves the users' confidence (Chapter 4).

Secondly, we provide design recommendations for the layout of Topic Maps. We describe which visual characteristics are important to the user, and how they can improve the users' confidence in interpreting and presenting Topic Map visualisations (Chapter 5).

Thirdly, we produce guidelines for the choice of mapping process when generating Topic Maps. These guidelines focus on the users' point of view in order to improve their confidence in explaining the process creating Topic Maps (Chapter 6).

Another major contribution of our work is the focus on users' confidence in their own ability to explain a visualisation system and the presentation of initial efforts towards understanding this confidence. We also present and implement a qualitative methodology to study this aspect of confidence, towards Topic Maps, and towards data visualisations in general (see Section 4.7).

This work also present additional minor contributions:

- We provide a design for layout mapping using an agglomerative clustering approach in Section 3.3.2.
- We draw out requirements for data visualisation Explanation Systems in Section 4.1.

1.5 Scope

This research specifically investigates the users' confidence in their ability to interpret and explain the automated layout mapping of Topic Maps. We not cover the effects of different topic modelling algorithms on user confidence, e.g. Latent Semantic Analysis (LSA) [25], Latent Dirichlet Allocation (LDA) [12], or Explicit Semantic Analysis (ESA) [38]), or the users' confidence towards topic models in general.

Furthermore, we restrict our research to mapping processes that produce regular Topic Maps, that lay out topics on a regular grid.

We also restrict our research to the user's confidence in explaining Topic Maps to themselves and third parties, i.e. we do not investigate the user's trust in the topic models, the system providers or other system characteristic.

Finally, we wish to distinguish between the terms Topic Maps and *concept maps*. Concept maps, as described by Trochim [103], are the result of a collaborative brainstorming and manual card sorting activities. These layouts are generated by the collaborators, and in general do not use automated systems. We restrict the investigation here to the use of automatic layout generation for topic models.

1.6 Organisation

This thesis is divided in seven chapters, as illustrated in Figure 1.2. This chapter (Chapter 1) sets out the motivations, goal, objectives, and scope for this research, and presents the methodology used and the contributions of this research. Chapter 2 presents the current state of the art methods for creating an arrangement of topics, and how previous research has addressed confidence, interpretability and explanations. The methods found in Chapter 2 are then applied in Chapter 3, which describes the topic modelling and mapping processes, together with the dataset used for this research.

The following three chapters (Chapters 4 to 6) consecutively report on the three studies conducted. The first focuses on interactive data-driven Explanation Systems. The second investigates characteristics of Topic Map layouts. Finally, the thirds explores the mapping processes themselves. Together they cover the research objectives we highlight above. As shown in Figure 1.2, Chapters 5 and 6 are both ensuing the results presented in Chapter 4, these two chapters can therefore be read independently of each other.

We conclude in Chapter 7 by summarising our contributions and findings.

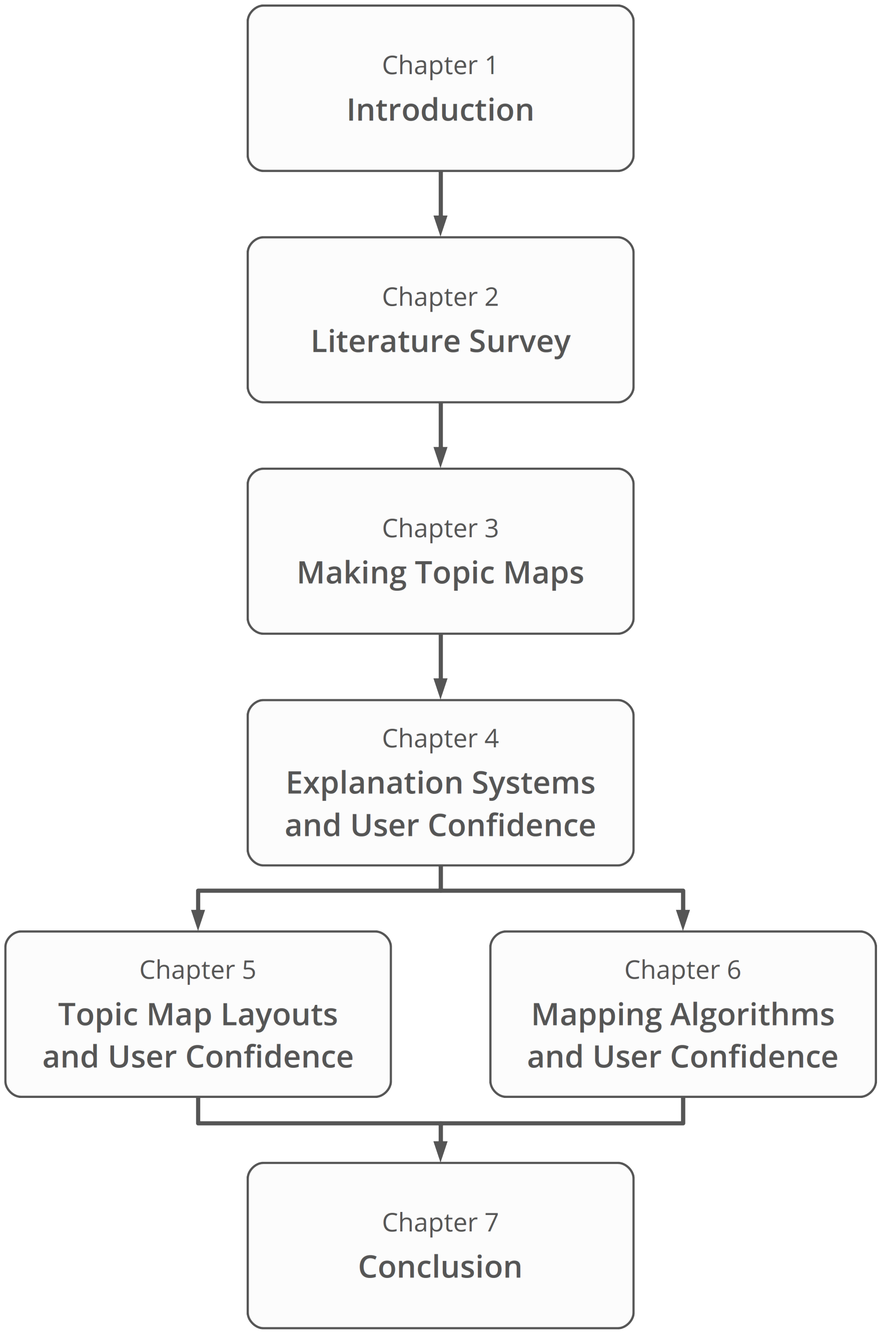

Figure 1.2: Organisation of chapters in this thesis, divided in three stages: Chapters 1 to 3 give context for the studies, Chapters 4 to 6 describe and report on the studies, and finally Chapter 7 conclude this research. Chapters 5 and 6 both follow up on Chapter 4. We present them in chronological order, but they can be read independently.

Chapter 2

Literature Survey

We split this review of the literature into two parts. Firstly, we explore the current state of the art in mapping information (Section 2.1). Secondly, we look into issues related to confidence, system interpretability, and explanations (Section 2.2). In Section 2.3 we conclude this survey and highlight how we situate our work within the literature.

2.1 Automated Layout Mapping

In this section we first establish the Topic Map properties that we are considering for the rest of this thesis (Sections 2.1.1 and 2.1.2). We then present the existing techniques in the literature for information mapping in Sections 2.1.3 and 2.1.4.

2.1.1 Relational Maps

The purpose of Topic Maps, and concept maps in general, is to display not only concepts, but more importantly the relationship between these concepts [21]. Van Gog et al. [105] describe three types of relations: hierarchical, causal/sequential, and semantic (see Figure 2.1). Our work focuses on using similarity, a semantic relationship, to organise topics. This relationship is also generally used for the manual generation process of concept maps [103], we however concentrate on automatically generated Topic Maps.

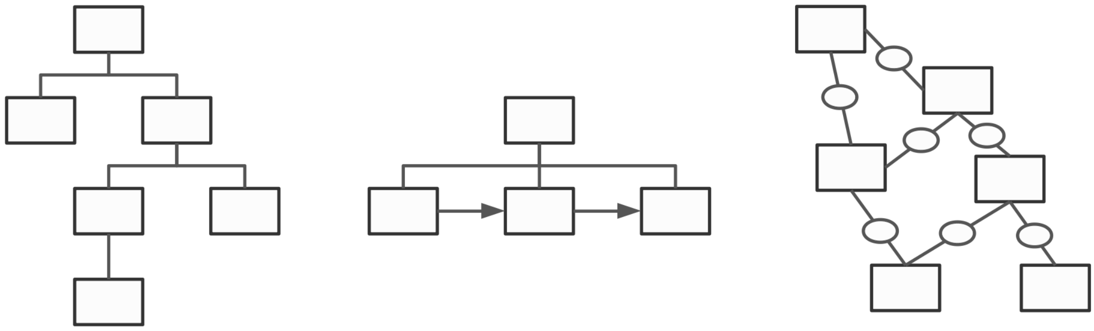

Figure 2.1: Illustration of the different relationships found in concept maps as presented by Van Gog et al. [105]. In this thesis we focus on a semantic relationship characterised by similarity between topics.

2.1.2 Hexagonal Grid Layouts

The regularity of grid layouts offers many advantages. First, mapping information onto regular grids aids users scanning and parsing it, by offering predictability in the spacial position of data [84]. As such it increases the readability of the layout [42]. Meanwhile, it offers aesthetically pleasing outputs as explained by Emmer [29]. Finally, showing division of the map with similar shape and size allows to avoid label overlap problem caused by the unknown provided space dimensions, as explain by Gansner et al. [40]. As such we will focus our research on regular layout mapping.

There are however limitations in using regular grids. Mainly, grid layouts provide a discrete space, while our proximity data (similarity) is continuous, and concerns can be raised regarding the veracity of such representation. We however argue that in all cases, multi-dimensional data can never be accurately represented on two-dimensional visualisations. As such, we need to acknowledge the necessity of a trade-off between readability and accuracy. This research will focus on visualisations with a trade-off set to provide a better readability.

There are three possible regular tesselation in a Euclidean plane using identical units: triangular, square, and hexagonal [47]. In comparison to the other options, hexagonal units offer a higher connectivity between items, allowing us to improve accuracy, while keeping the same level of readability. In addition, using hexagonal grids allows to maximise space utilisation. As such they are often seen in nature (e.g. beehives, bubble packing, compound eyes of insects, or snowflakes) because of these properties, as demonstrated by the Honeycomb conjecture [50].

2.1.3 Reductive Approaches

In this section we review the *reductive* methods of layout mapping. We define these methods as those which take into account all of the available similarity information to output the optimal solution from a set of possible arrangements. There are numerous examples of such methods used to visualise text content [15, 24, 110], Gansner et al. and Mashima et al., for instance, make use of geographical map metaphors [39, 76].

The core of these examples relies on projection based methods. Such methods "project" multidimensional data onto 2D arrangements and retain the one arrangement displaying the most information. Amongst these are linear methods, like Principal Component Analysis (PCA) [56] and Multidimensional Scaling (MDS) [64], and non-linear methods such as Locally Linear Embedding (LLE) [96] or Isomap [102]. Force-directed graph drawing [37] presents an alternative to these projection methods. This method relies on balancing forces between items, using translation vectors: repulsive forces between all items, and attractive forces between linked or similar items.

Projection based and force-directed methods however produce results in continuous space, making irregular layouts.

Self-Organising Map (SOM) [63] is a dimensionality reduction technique that overcomes this issue, and organises data into a grid. It however causes items to overlap. Self-Sorting Map (SSM) [101] is another example of dimensionality reduction that results in a discrete arrangement of items, but those results are constrained by fixed and predetermined grids.

Freid et al. [36] and Gomez-Nieto et al. [42] separately presented an alternative approach. It uses the results of dimensionality reduction processes, and creates a regular grid in the same space. The regular layout result is then resolved using an assignment algorithm, such as the Hungarian algorithm, or Kuhn-Munkres algorithm [82].

As it uses dimensionality reduction, this method is representative of most reductive mapping process techniques. It also offers the possibility to generate regular Topic Map layouts, while allowing flexibility for the grid shape, and avoiding overlapping items. These attributes make it our foremost choice as representative of reductive approaches for our research. In this research, we will denominate it: projective mapping process.

The same concerns raised in the previous section (Section 2.1.2) could apply to this method, that is, whether assigning projected items to unique grid-cells decreases the accuracy of the visualisation. To which we argue that the gain in readability justifies this choice. Furthermore, in comparison to other reductive methods, the grid generation is determined by the result of the dimensionality reduction process, making it more accurate.

2.1.4 Constructive Approaches

In their study, Padilla et al. looked into users' behaviours and logic when organising ideas into concept maps [88]. They describe their observation as follow: "*The distance similarity data created by dimensionality reductions algorithms [...], might be overlooked by users.*" (Padilla et al.) It led to this recommendation: "*Use local similarity information in preference to long-distance similarity when designing or creating algorithms for visualisations.*" (Padilla et al.)

Despite these findings only little of the literature proposes constructive approaches for layout mapping, that is, approaches building relations between items, as described by Novak and Cañas [85], and gradually adding complexity in the map layout.

Incremental Board, from Pinho et al. [91], follows this approach. It gradually builds a layout by first overlapping items with their most similar item already in the layout, and then displacing items in the layout to remove overlaps while minimising the error. This framework is however designed to suit dynamic data sets.

Hierarchical clustering [95], and particularly agglomerative clustering, offers the possibility to compute the relations between items. We believe that this hierarchical structure can be used to organise items into a grid. To our knowledge, however, the literature does not propose the use of agglomerative clustering for layout mapping purposes. We initiate such usage for this thesis, and make agglomerative clustering our representative constructive approach.

2.2 Confidence, Interpretability, and Explanations

2.2.1 Confidence

The user's trust and/or confidence in algorithmic interfaces have been studied in many computer science fields, particularly in the fields of Machine Learning (ML) and automation [26, 41, 61, 93]. Notably, trust in recommender systems has received a lot of attention [20, 53, 62, 70].

In recent years, with the rise of concerns regarding privacy and security, researchers in Human-Computer Interaction (HCI) have accentuated their investigation in trust towards the automated use of personal data [43, 97, 98, 106]. It led to clearer trends in trust and digital profiling [108], targeted advertisement awareness [23, 30], or algorithmic fairness [111].

Trust evaluation has been integrated in the studies of novel visualisation systems [33, 81]. But to our knowledge, with regard to automated visualisation processes, no research has placed the exploration and analysis of users' trust or confidence as their primary goal.

The work we refer to above investigated trust and confidence indistinguishably. The differences between trust and confidence have however been long explored in sociology and managerial sciences [74, 78]. In the context of human interaction with computer systems, Pieters presents a distinction between the two concepts as follow [90]: "*A system acquires confidence if it is reliable, and it acquires trust if it is trustworthy. [...] Before they give their trust to a system, people will perform a risk analysis. People who establish confidence in a system do not do this. In this sense, it is harder for a system to acquire trust than to acquire confidence. However, maintaining trust is easier than maintaining confidence.*" (Pieters)

Our motivation is to provide non-technical users with designs helping them support their decisions. We believe that providing a full risk-assessment would be inadequate in this context. We will hence focus towards raising the interpretability and explainability of Topic Maps and making them more reliable for non-technical users, which impacts their confidence, as per Pieters's definition.

We however propose to differentiate between two distinct, but strongly linked, aspects of user confidence. To our knowledge, when discussing user confidence, previous research as emphasised on the confidence of a user towards a system. Here, we introduce a novel facet to confidence, and consider it as the perception of a user towards their own ability to interpret and explain the system (i.e. the Topic Maps).

2.2.2 Interpretability

The matter of confidence in visualisations can be linked with Visualisation Literacy (VL), i.e. the ability to interpret visualisations. Research in this area has established ways of measuring VL [14,67], or assessed levels of VL in populations [13]. We however argue that the work presented in these papers is limited as to our research focus. Beyond the interpretability of Topic Maps, we wish to investigate the interpretability of the layout mappings processes, and their impact on user confidence.

The matter of interpretability in, and explanation of, algorithmic processes is not a novel problem, particularly with artificial intelligent agents [6, 22]. The rapid advances in the fields of Artificial Intelligence (AI), Machine Learning (ML), or Deep Learning (DL), however came with slow progress for interpretability, and such systems were qualified as “black-boxes”, a term highlighting their lack of transparency. The recent advocacy for personal data ethic however re-established concerns for interpretability and explainability, for example with the European General Data Protection Regulation (GDPR) [31].

Progress for interpretability and explainability in ML have been pursued, for example by Kim, Lisboa, and Nugent and Cunningham [57,69,86], and recent workshops attest of the growing interest in these issues [3, 58, 75]. Kulesza et al. notably present an explanatory interface for interactive Machine Learning [65]. These efforts led to the emergence of Explainable Artificial Intelligence (XAI) as a new field of research [48].

This trend did not leave the HCI community aside, notably with the expansion of social media and the collection and manipulation of personal data. Hamilton et al., for example, studied the interpretability of algorithm in social media feeds [51]. Alvarado et al. introduce the concept of Algorithmic Experience (AX) to describe the user perspective on algorithms [5], while focusing on the user perception of targeted advertisement. Prior to this work, however, we have not encountered research made in the interpretability of visualisation processes.

2.2.3 Explanations

It is common to implement explanations to aid interpretability [5, 22, 48, 65, 86]. Among others purposes, algorithm explanations have been used to: justify for decisions [92], aid data exploration [17], and highlight differences between preconception and reality [59].

Gregor and Benbasat provide a detailed meta-review and classification of explanations in the context of knowledge-based systems [44]. Their classification followed three dimensions: content type, presentation format, and provision mechanisms. Four types of contents are highlighted:

- *Reasoning Trace*: exposing, per case, the system’s line of reasoning;

- *Justification*: attaching "deep" knowledge to specific parts of the reasoning process;
- *Strategic*: providing the system's strategy;
- *Terminology*: defining terms.

Given our target user group (i.e. non-technical), we believe that terminology and strategic explanation are not sufficient to improve their knowledge of layout mapping, and therefore their confidence. Furthermore, looking back at our informal discussion with research managers, we argue that giving justification for parts of the system does not provide users with enough background to contextualise the explanations. We will therefore focus our work on reasoning trace explanations for mapping process.

Lim et al. proposed to further the study of these reasoning trace explanations, by posing five intelligibility questions: *what* did the system do?, *why* did the system do W?, *why not* doing X?, *what if* the system did Y?, and *how to* achieve Z? [68]. Their results suggest that explanations concentrating on resolving the *why* intelligibility question performed better for novice users. We will therefore aim at providing such explanations for mapping process.

Two formats of explanations are highlighted by Gregor and Benbasat: *Text-based* and *Multimedia*. In our work, the subject of the explanation, Topic Maps, are shown on multimedia supports, i.e. visualisations. As per Mayer and Moreno's coherence principle [77], using a text explanation (verbal) for a multimedia subject (visual) will cause a cognitive overload, we will therefore focus on visual explanations.

By designing and using explanations of mapping processes, we aim at studying the impact on their interpretability, the interpretability of Topic Maps, and the confidence of users in their ability to restitute that knowledge. To carry out this research we will therefore adopt an *Automatic* provision mechanism for our explanations (as opposed to *User-involved* and *Intelligent* in Gregor and Benbasat's classification).

2.3 Conclusion

The current state of the art in layout mapping highlights the predominance of reductive approaches, mostly relying on dimensionality-reduction, or projection based, methods (Section 2.1). Combined with grid generation techniques and assignment algorithms, they provide suitable candidates for the layout mapping stage of Topic Maps generation. In this survey, we have however also found that constructive approaches can offer an alternative, despite their lack of presence in the literature. Increasing the range of mapping process stimuli for our studies will also allow for better and more insightful results.

In the next chapter, Chapter 3, we present the generative process of automated Topic Map layouts. After presenting the data collection and topic generation processes, we will describe the implementation of two mapping processes: one reductive, or *projective*, that we have identified in this survey, and one constructive, or *agglomerative*, that we develop.

The second part of our survey (Section 2.2) presents the research conducted in confidence, interpretability and explanation mechanisms. We found that there is a growing interest to provide users with interpretable algorithms and concern to raise their confidence in those algorithms. While studies have targeted domains such has digital profiling through Machine Learning techniques, no work has been carried out towards user confidence and automated visualisations to our knowledge. In addition, we suggest a novel definition of user confidence, i.e. the self-perception of one's ability, and propose it as the focus of our research.

The literature describes many classifications of explanation mechanisms, based on their medium, content, or objectives. In particular, we have identified that visual reasoning trace explanations, answering *why* questions, are better suited for explaining visualisations to our target audience, i.e. non-technical users.

We describe our Explanation Systems design in our first study chapter, Chapter 4.

Chapter 3

Making Topic Maps

For our studies, we have implemented our own Topic Maps. Three types of applications were used to automatically generate the required data for these visualisations. This chapter describes the processes behind these applications. Figure 3.1 shows how these applications interconnect and communicate data.

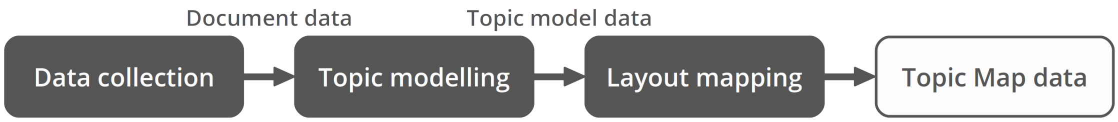

Figure 3.1: Flowchart of the applications producing Topic Map data. We distinguish between three types of application: data collection, topic modelling, and layout mapping, of which we have developed two: one projective and one agglomerative.

First we will describe the choice of data and the data collection process in Section 3.1. We then introduce the topic modelling application in Section 3.2. Finally, Section 3.3 presents the implementation of the two layout mapping applications we have identified in 2.1.

3.1 Data Collection

To simulate authentic Topic Maps and real world scenarios [10, 55], we have decided to use research grant data for our studies. This type of data comprises of well defined, yet highly related topics.

We used Gateway to Research (GtR) [104] to collect our data, released in July 2012 [18] by United Kingdom Research and Innovation (UKRI)[1]. This open portal consist of a joined database of publicly funded projects from nine British national research organisations. It also provides Application-Programming Interfaces (APIs), which allow for an easy access to the database.

At the time of the data collection phase, the GtR database had aggregated more than 60,000 research project entries. We decided however to only collect data from the Engineering and Physical Science Research Council (EPSRC) to fit with our participants pool's interests (our participants were recruited using convenience sampling). This also allowed us to focus the Topic Maps' themes, create more contentious visualisations, and get better insights.

We implemented a script designed to access GtR's API, retrieve research projects' information (using a list of project identifiers[2]), and save the information in data files. A total of 14,083 project descriptions were downloaded, on the 23rd of June 2016. In those descriptions, we identified two fields containing the project's main themes: the grant title and the grant abstract (Figure 3.2). Extracting those themes, or topics, was done by means of topic modelling, which we describe in the next section.

3.2 Topic Modelling

This section describes our topic modelling application. It is designed to output two data structures from the project descriptions: *a*) the list of topics, described with labels, and *b*) the dissimilarity information between topics. It is divided into three main processes: lemmatisation, collapsed Gibbs sampling, and cosine dissimilarity measure (Figure 3.3).

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[1] UKRI was then known as Research Councils UK (RCUK)

[2] The list of identifiers is available on GtR's website [104]. Details on how to use the API are available in the documentation: http://gtr.ukri.org/resources/api.html. Accessed May 9th 2018.

Document 1

Title: "Perceptual Measurement of Surface Texture"

Abstract: "Surface appearance is a critical characteristic of nearly all of today's commodity items and plays an important role in many other aspects of our lives. While internationally accepted standards have been defined for the measurement of colour and instruments are available for the measurement of surface gloss, there are no accepted ways of measuring the complex phenomenon we know as 'texture'.A small number of studies have sought to develop perceptually meaningful methods for measuring texture. However, we believe that these experiments were significantly flawed by the use of incomplete stimuli and uncontrolled conditions (they employed still photographs of surfaces imaged under unknown illumination conditions). Our proposal differs fundamentally from previous work because: a) we will compute texture measures directly from surface descriptions rather than from images / thereby removing the significant biasing effects illumination, and b) we will use graphics shader technologies to provide real-time photorealistic visualisations of real surface textures / this will provide both rich stimuli for the observers and full control over the psychophysical experiments.We believe that this work is of international significance because it tackles the important scientific problem of providing repeatable methods for obtaining perceptually meaningful measures of texture, and that with the collaboration of NPL and CIE it will establish the basis for national and international standards for texture measurement."

URL: "http://gtr.ukri.org/projects?ref=EP%2FD059364%2F1"

Document 2

Title: "ICT Perspectives (an ICT Next Decade proposal)"

Abstract: "This project will provide new ways of viewing EPSRC's ICT (Information and Communications Technology) portfolio to enable researchers, EPSRC staff and other stakeholders to better contribute to ICT strategy.

The project is divided into two main stages. The first will develop new 'Perspectives' on the current portfolio based on existing 'Grants on the Web' data, the second will use spinout workshops to kick-start the use of the Perspectives and provide feedback on best practice from cross-ICT meetings.

In the first phase we will use text mining and simple visualisation techniques to provide 'at a glance' overviews of the portfolio in the form of word-clouds or similar intuitive presentations. All terminology will be derived from the community, either from the grant summaries and titles or by canvassing the community directly. The 'at a glance' views will also provide the top level of an intuitive navigation system which will allow users to rapidly drilldown to project and investigator descriptions using the natural structure inherent in 'Grants on the Web' and derived using text mining.

As well as being viewable on the web these Perspectives will also be available as a set of standalone materials and associated tools for ICT strategy and Network workshops. They will provide an accessible overview of the portfolio and its natural structure. The latter will be presented in interactive dendrogram form to allow easy partitioning for scoping more detailed workshop breakout sessions.

The second phase of the project will focus on networking. Six 'spinout' workshops will be organised by open call that will make use of Perspectives' materials and tools to facilitate brainstorming and road-mapping type activities. Meetings that bring together two or more Networks will be especially sought."

URL: "http://gtr.ukri.org/projects?ref=EP%2FI038845%2F1"

Figure 3.2: Example of two documents downloaded from GtR. We have included the links to the corresponding GtR pages for reference (accessed June 7$^{\text{th}}$ 2018), this information was however not used for the creation of Topic Maps.

Lemmatisation

A lemmatisation aims at processing textual data in order to extract the keywords from it in their dictionary form. To this end, we first created a list of our research documents, with each entry being a concatenation of the project title and abstract. The texts then go through three preliminary stages.

1. Tokenising: Separating the text into a list of words using a regular expression.
2. Cleaning: Removing stop-words from the list of words. The stop-words comprised of common English stop-words (e.g. "the", "and", "that"), and a custom list of terms retroactively updated to limit the emergence of generic topics [16].
3. Tagging: Assigning words with their part-of-speech (PoS) categories (e.g. noun, adjective, verb). To reduce future processing time, and get more meaningful topics, we only kept nouns at this stage.

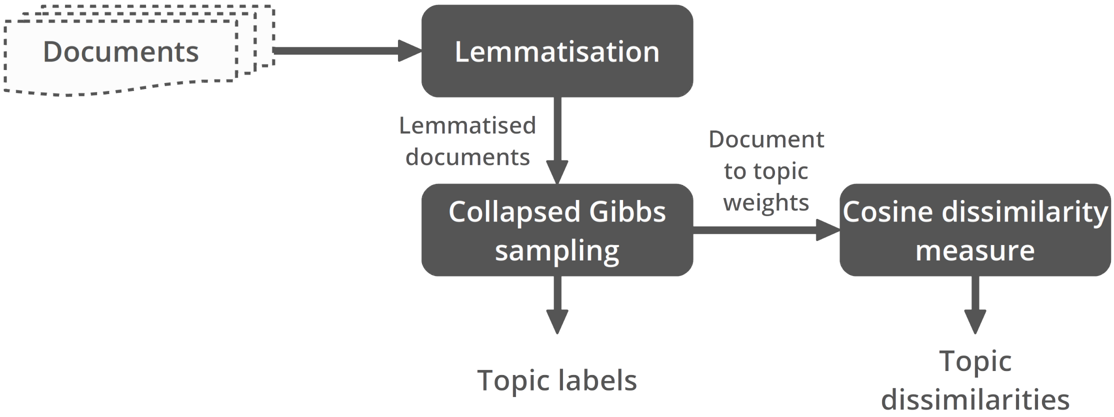

Figure 3.3: Flowchart of the topic modelling application. This application takes a list of documents as input and outputs a list of topic labels, and a topic to topic dissimilarity matrix. The data goes through three main transformations: lemmatisation, collapsed Gibbs sampling, and cosine dissimilarity measure.

The lemmatisation then extract the lemmas, or dictionary forms, of PoS-tagged words using the WordNet lexical database [80]. The output of this process is the lemmatised document list L, each entry now comprising of the list of lemmatised words in the project title and abstract (Figure 3.4).

Collapsed Gibbs Sampling

To sample topics, i.e. find latent themes in the lemmatised documents, the topic modelling application uses LDA [12] by applying collapsed Gibbs sampling [46].

LDA describes a generative process for documents, over topics and a vocabulary:

$$\begin{aligned} &\theta(t|d) \sim Dir(\alpha) \\ &\upsilon(i,d) \sim \theta(t|d) \\ &\phi(w|t) \sim Dir(\beta) \\ &\omega(i,d) \sim \phi(w|\upsilon(i,d)) \end{aligned} \tag{3.1}$$

$Dir(\alpha)$ and $Dir(\beta)$ are both Dirichlet distributions. They respectively sample two multinomial distributions θ and ϕ. $\theta(t|d)$ represents the probability of having topic t in document d. $\phi(w|t)$ is the probability of having word w in topic t. To generate

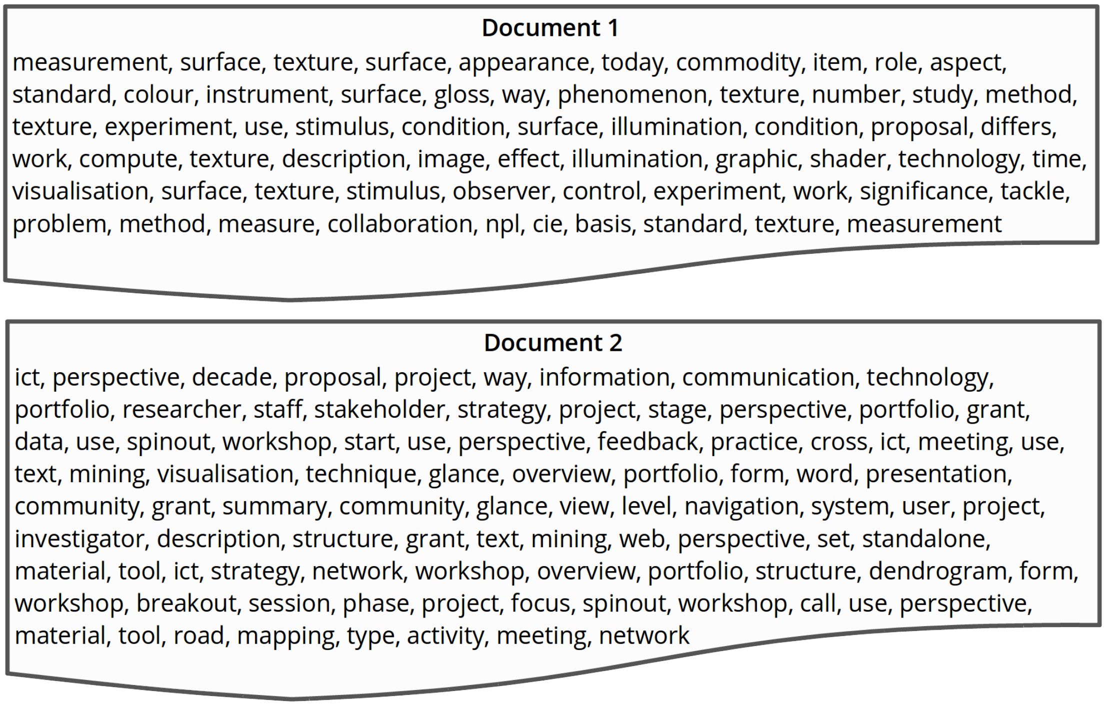

Figure 3.4: Example of two lemmatised documents (same documents as in Figure 3.2) as outputted from the lemmatisation process.

a document d, each i^{th} token in the document is given a topic assignment $\upsilon(i,d)$, with a probability of $\theta(t|d)$ for topic t. Then, the token is assigned a word value $\omega(i,d)$ from topic $\upsilon(i,d)$, with a probability of $\phi(w|\upsilon(i,d))$ for word w.

Our goal is to train this generative model with L, which describes ω. Thus we need to sample the topic assignment υ. Collapsed Gibbs sampling does so, by integrating out θ and ϕ, and sampling the conditional probability of $\upsilon(i,d)$, in an iterative manner, for each token i in all document d:

$$P(\upsilon(i,d) = t|\upsilon^{\neg i,d}, \omega, \alpha, \beta) \propto ({\upsilon_{count}}^{\neg i,d}(t,d) + \alpha)\frac{({\omega_{count}}^{\neg i,d}(\omega(i,d),t) + \beta)}{(\sum_w \omega_{count}(w,t) + \beta)} \tag{3.2}$$

The fundamental principles behind collapsed Gibbs sampling is to get the probability of assigning a token i from document d to topic t $(P(\upsilon(i,d) = t))$ for each topic. These probabilities are derived from the observations of the topic proportions in the document $({\upsilon_{count}}^{\neg i,d}(t,d))$, and the token's value proportions in the topics $({\omega_{count}}^{\neg i,d}(\omega(i,d),t))$. The assignment is then randomly picked from this probability distribution. $\upsilon_{count}(t,d)$ and $\omega_{count}(w,t)$ are respectively the number of token in document d assigned to topic t, and the number of tokens with value w in topic t.

The superscript $\neg i, d$ describes the exclusion of the observed token from the count values.

From this sample, two data structures result:

- the per-topic word distributions Φ ($\Phi_{t,w}$ is the weight of word w in topic t);
- the per-document topic distributions Θ ($\Theta_{d,t}$ is the weight of topic t in document d).

Cosine Dissimilarity Measure

In order to position topics on a Topic Map, we need to compute the similarities, or dissimilarities between topics. Most research uses word vectors in the topic space to estimate topic similarity [4]. However given that our goal is to summarise the document portfolio, we want the similarity between topics to represent their co-occurrences in documents: topics with the same proportions in the same documents are semantically closer to one another. We therefore decided to look at cosine dissimilarity between topic vectors in the document vectors.

We start this process by eliminating the "noise" in Θ, i.e. the low topic weights in documents. We do so by filtering the relevant documents d for each topic t in the list U:

$$d \in U_t \iff \Theta_{d,t} > \text{avg}({\Theta^{-1}}_t)m \tag{3.3}$$

Where m is a multiplier that we decrement (starting value is 10) until one or more documents are found.

We then calculate V, the list of topic vectors in topic space. $V_{t,t'}$ is set to be the normalised sum of topic t''s weights in all documents d relevant to topic t:

$$V_{t,t'} = \frac{\sum_d^{U_t} {\Theta^{-1}}_{t',d}}{|U_t|} \tag{3.4}$$

Finally we can compute the topic to topic dissimilarity matrix D using the cosine dissimilarity formula. We do so for each pair of topic t and t', using their respective vector in V:

$$D_{t,t'} = 1 - \frac{\sum_u V_{t,u} V_{t',u}}{\sqrt{\sum_u {V_{t,u}}^2} \sqrt{\sum_u {V_{t',u}}^2}} \tag{3.5}$$

Outputs of the Topic Modelling Application

The topic modelling application outputs two data structures (see Figure 3.5):

- the list of topics T;
- the topic to topic dissimilarity matrix D.

Each topic in T comprises of one identifier, and three attributes. One of those attributes is the list of labels in the topic, which we get from Φ. The other two attributes, the Topic Map coordinates and the cluster identifier, are results of a mapping process implemented by a layout mapping application.

Topics

Topic 1	
use	(0.0545)
perspective	(0.0454)
workshop	(0.0364)
system	(0.0364)
project	(0.0364)

Topic 2	
quantum	(0.0951)
measure	(0.0571)
entanglement	(0.0381)
limit	(0.0286)
method	(0.0286)

Topic 3	
reactor	(0.0555)
component	(0.0463)
carbon	(0.0463)
temperature	(0.0278)
length	(0.0278)

Topic 4	
texture	(0.0521)
surface	(0.0435)
number	(0.0261)
visit	(0.0261)
standard	(0.0261)

Topic 5	
electron	(0.0850)
material	(0.0744)
layer	(0.0532)
study	(0.0425)
semiconductor	(0.0425)

Topic dissimilarities

	1	2	3	4	5
1	0	0.888	0.996	0.942	0.858
2	0.888	0	0.986	0.788	0.897
3	0.996	0.986	0	0.961	0.810
4	0.942	0.788	0.961	0	0.903
5	0.858	0.897	0.810	0.903	0

Figure 3.5: Example of the topic modelling application outputs. Each topic comprises of a list of labels, weighted to reflect their importance in their respective topic. These 5 topics were extracted from 6 documents, which explains the high dissimilarities. In practice we can extract tens or hundreds of topics from thousands of documents.

3.3 Layout Mapping

The purpose of a layout mapping application is to produce mappable topic information. That is, augment topics (T) with position and cluster information, which are both derived from the topic dissimilarity measures (D).

As described in the survey chapter, we decided to implement two mapping processes, in order to introduce variety in the stimuli presented to participants. The first is a reductive method, that we label "*projective mapping process*". The second is a constructive method, that we label "*agglomerative mapping process*". This section presents their implementations.

The position information is computed with the aim of producing hexagonal Topic Maps, where each topic is represented by an hexagon cell. Details on hexagonal grids can be found in Appendix A, page 123.

3.3.1 Projective Mapping Process

This mapping process follows the implementation of IsoMatch, as described by Fried et al. [36]. It uses four main processes (see Figure 3.6). To obtain the position, we use the following processes: dimensionality reduction (Isomap), grid generation, and finally assignment (Hungarian algorithm). The cluster information is obtain by applying k-means after the dimensionality reduction process.

Isomap

The first step in producing Topic Maps with the projective mapping process is to make a projection of the topics in two dimensions, using the dissimilarity matrix D (which is $|T|$-dimensional). Applying a dimensionality reduction algorithm onto D allows to create such projection, while preserving the most relevant information.

We chose to use Isomap [102] for this purpose, as suggested by Fried et al. Isomap follows three steps:

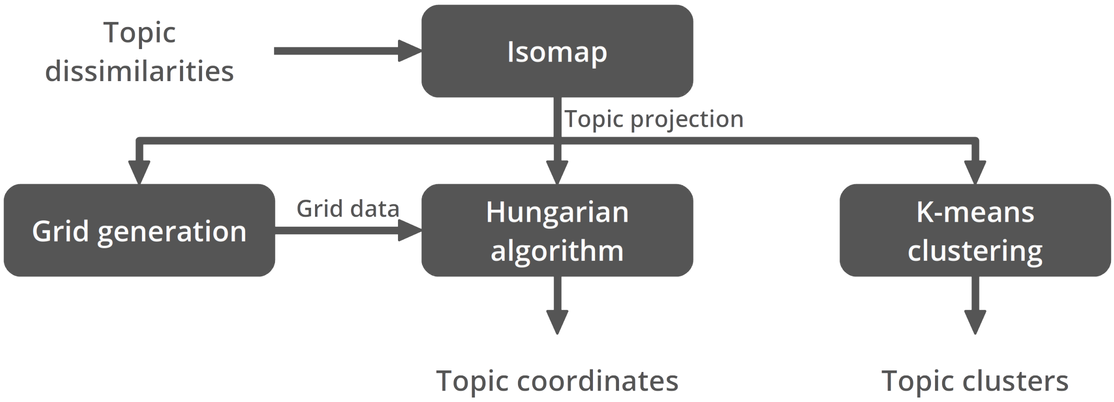

Figure 3.6: Flowchart of the layout mapping application implementing the projective mapping process. This application takes the topic dissimilarity information and applies Isomap to produce a topic projection. Then the grid generation process and Hungarian algorithm produce topic coordinates. Using k-means on the topic projection produces the clustering information.

1. Build a topic neighbour graph Γ from D. In Γ, each vertex is a topic, connected to its n nearest-neighbours in D. The edge weight between vertex t and t' is $D_{t,t'}$.
2. Build the graph distance matrix δ. $\delta_{t,t'}$ would represent the shortest distance between topic t and t' in Γ. This can be achieved using Floyd's algorithm [35]:
   (a) For each pair of topics t and t', set $\delta_{t,t'}$ to the weight of the edge $\{t, t'\}$ in Γ if such edge exist, otherwise set it to ∞.
   (b) For each intermediate topic u, and for each pair of topics t and t', set $\delta_{t,t'}$ to the lowest value between $\delta_{t,t'}$ and $\delta_{t,u} + \delta_{u,t'}$.
3. Compute the multi-dimensional embedding O of δ. This requires to first convert distances to inner products using the τ operator (Equation (3.6), C represents the centring matrix). Then given the list of eigenvalues λ and eigenvectors ν (in decreasing order) of $\tau(\delta)$, we estimate O as shown in Equation (3.7) (λ_p is the p^{th} eigenvalue, and ν_{p_t} is the t^{th} value of the p^{th} eigenvector).

$$\tau(\delta) = \frac{-C\delta^2 C}{2} \tag{3.6}$$

$$O_{t,p} = \sqrt{\lambda_p \nu_{p_t}} \tag{3.7}$$

This outputs a list of tuple, O_t expressing the coordinates of topic t in $|O|$ dimensions. We then compute P, the two-dimensional embedding, as a subset of O, the value of P_t being $(O_{t,1}, O_{t,2})$ for each topic t.

Grid Generation

The second step of the projective mapping process is to generate an hexagonal grid G in the same space as P. To decide on the position of this grid we look at the inter-quartile range of both axes in P and create a bounding box B, its attributes being defined as follow:

$$\begin{aligned} B_x &= q_1(P_x) - f_s(q_3(P_x) - q_1(P_x)) \\ B_y &= q_1(P_y) - f_s(q_3(P_y) - q_1(P_y)) \\ B_{width} &= q_3(P_x) + f_s(q_3(P_x) - q_1(P_x)) - B_x \\ B_{height} &= q_3(P_y) + f_s(q_3(P_y) - q_1(P_y)) - B_y \end{aligned} \tag{3.8}$$

$q_1(P_x)$, $q_3(P_x)$, $q_1(P_y)$, and $q_3(P_y)$ are the first and third quartiles on the x and y axes in P. We control the size of this box using the factor f_s. Figure 3.7a illustrates this process with an example.

Then we estimate the best combination of number of rows G_{rows} and number of columns G_{cols}, given a target number of cells $G_{cells} = f_c|T|$, where f_c is factor greater or equal to 1 used to introduce noise in the Topic Map. We estimate G_{rows} and G_{cols} by looking at all the pairs of integer factors of G_{cells}, and choosing the couple with a ratio closest to the width and height ratio of B. If the ratio difference is more than 0.05, no solution is found, G_{cells} is incremented, and the process reiterated.

Finally we construct the hexagonal grid G of size $G_{rows} \times G_{cols}$. This process starts by computing the size s of the hexagons in G as shown in Equation (3.9). Each hexagon $G_{r,c}$ is then assigned coordinates, every other row of hexagon being offset, as shown in Equation (3.10). The example in Figure 3.7b corresponds to this part of the process.

$$s = \begin{cases} \dfrac{B_{height}}{\frac{3}{2}(G_{rows} - 1)} & \text{if } G_{rows} \neq 1 \\ B_{height} & \text{otherwise} \end{cases} \tag{3.9}$$

$$\begin{aligned} G_{r,c_x} &= \begin{cases} B_x + \sqrt{3}sc & \text{if } r \text{ is even} \\ B_x + \sqrt{3}sc + \dfrac{\sqrt{3}}{2}s & \text{if } r \text{ is odd} \end{cases} \\ G_{r,c_y} &= B_y + \frac{3}{2}sr \end{aligned} \tag{3.10}$$

Hungarian Algorithm

The last step of the projective mapping process is to produce a discrete hexagonal layout by mapping topic points from P to grid cells in G, while minimising the total cost of "*moving*" topics. As G is build in the same space as P, we solve this step with an assignment algorithm, such as the Hungarian (or Kuhn-Munkres) algorithm [82].

We first create δ', the Euclidean distance matrix between topic points in P and cells in G (Equation (3.11)). Since $G_{cells} > |T|$ (because of f_c), we add rows with values set to zeros to make δ' square. The algorithm then proceed as follow to find an optimal assignment of topic to grid cell:

1. For each row in δ' subtract its smallest value from all of its values.
2. For each column in δ' subtract its smallest value from all of its values.
3. Find the minimum number of lines (vertical or horizontal) needed to cover all zeros in δ'.
4. Check for optimality:
   - If the minimum number of line is equal to the size of δ', an optimal assignment is possible, thus we stop.
   - Otherwise, proceed to step 5.

5. Find the smallest uncovered value in δ', subtract this value from uncovered rows, and add this value to covered columns. Then repeat from step 3.

$$dist_{eucl}(a, b) = \sqrt{(a_x - a_x)^2 + (b_y - a_y)^2} \qquad (3.11)^3$$

If an optimal assignment is possible (step 4), it can be estimated within the cells of δ' with value zero. Figure 3.7c shows an example result of this assignment.

This assignment allows to find the optimal coordinates of each topic in G, which we incorporate in T.

K-means Clustering

To find c topic clusters, we chose to use k-means clustering [72]. Using this algorithm allows to get clusters from P that would be visually compact.

K-means operates as follow:

1. Position c means in the same space as P, using the k-means++ algorithm [7].
2. Assign each topic in P to the cluster with closest mean, using the squared Euclidean distance (Equation (3.11)).
3. Reposition each mean as the centroid of their cluster.
4. Repeat steps 2 and 3 until there are no variation of mean.

The initial position of the means where estimated using the k-means++ algorithm [7]:

1. From the topic points in P, randomly choose one to become a mean.
2. For each t topic point in P, compute the Euclidean distance ϵ_k to the nearest mean (Equation (3.11)).

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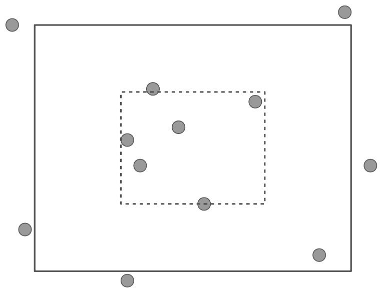
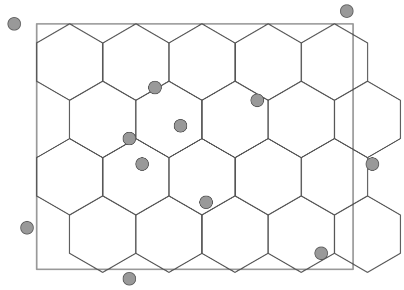
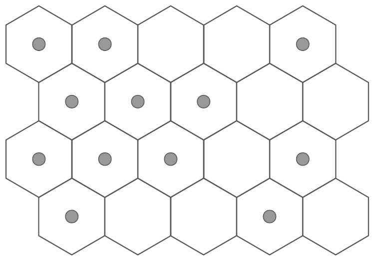
[3] This distance measure is reused multiple times in this implementation. We therefore present it in generic terms here. This shows the distance computation between two points a and b, in the same space, with two coordinates x and y each.



(a) Bounding box definition, the first and third quartile are represented with dashed lines, the bounding box (continuous line) is defined with $f_s = 0.6$.



(b) Grid generation, the initial number of grid cells was defined with $f_c = 1.5$, but got incremented twice to fit a grid with a closer ratio with the bounding box.



(c) Topic to grid assignment, each topic was mapped to the nearest possible unoccupied grid cell, while minimising the total mapping cost.

Figure 3.7: Example of a regular Topic Map produced from an irregular projection of topics. First, a bounding box is defined using interquartile ranges from the projection (Figure 3.7a). A grid is then generated within the bounding box (Figure 3.7b). Finally, the topic points are mapped to the closest grid cell (Figure 3.7c).

3. From the data points in P, randomly choose a new mean with a probability for each topic t proportional to ϵ_k^2.
4. Repeat steps 2 and 3 until c means have been found.

As with the coordinate data, we incorporate the cluster information in T, by adding a cluster identifier to each topic.

3.3.2 Agglomerative Mapping Process

This mapping process builds on top of the concept of hierarchical clustering [95]. There are two processes are at the heart of this mapping process (Figure 3.8). First the agglomerative clustering, and then the relative positioning, which uses the cluster hierarchy from the clustering process.[4]

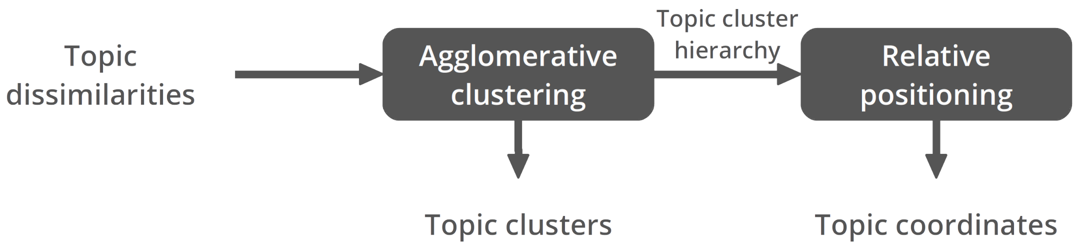


Figure 3.8: Flowchart of the layout mapping application implementing the agglomerative mapping process. This application takes the topic dissimilarity information as input and uses agglomerative clustering to produce a topic cluster hierarchy. The cluster information can be directly extracted from it. A second process uses the cluster hierarchy to position the topic in relation to each other, creating the topic coordinates.

Agglomerative Clustering

The first step of the agglomerative mapping process is to create a cluster hierarchy of topics, using agglomerative clustering [95]. This hierarchy can be expressed in the form of a linkage table ℓ, where each node in ℓ is a triple that comprises of two child nodes and the distance at which they join. Figure 3.9 shows an example of a linkage table represented as a dendrogram. We initialise ℓ with $|T|$ leaf nodes (one per topic), a leaf node having no child nodes and its distance set to 0. Each topic is then considered as cluster of their own, and the distances between those clusters are expressed in D.

The agglomerative clustering then iteratively collapse a clone of D, D', while populating ℓ:

[4]Mike J Chantler. An Agglomerative Layout Algorithm. *Unpublished, Private Communication.* 2016.

1. Find the couple (A, B) such that $D'_{A,B}$ is the minimum dissimilarity value in D', and $A \neq B$.
2. In the linkage table ℓ, add the node $(A, B, D'_{A,B})$.
3. In D', add the row and column $\{A, B\}$, the new values of $D'_{\{A,B\},\text{-}}$ and $D'_{\text{-},\{A,B\}}$ are estimated using the complete linkage formula [60] (Equation (3.12), with t and t' being individual topics in the clusters).
4. Remove the rows and columns A and B from D'.
5. Repeat from step 1, until $|D'| = 1$.

$$D'_{A,B} = \max_{t \in A, t' \in B}(D_{t,t'}) \tag{3.12}$$

Although other linkage criteria are available, we chose the complete linkage as it produces more uniform clusters. The last node added to ℓ, ℓ_{root}, is the root of the hierarchy.

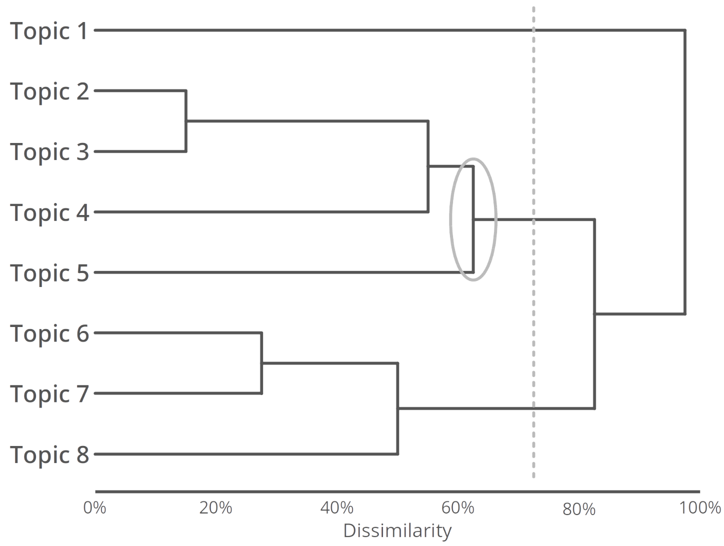
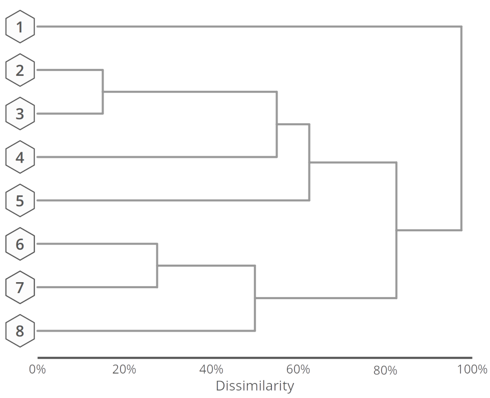


Figure 3.9: Example of a linkage table, represented by a dendrogram. The circled node joins clusters $\{2, 3, 4\}$ with cluster $\{5\}$ at distance 0.625 or 62.5% dissimilarity. The dashed line represent the "cut" to get three clusters from the hierarchy: $\{1\}$, $\{2, 3, 4, 5\}$, and $\{6, 7, 8\}$.

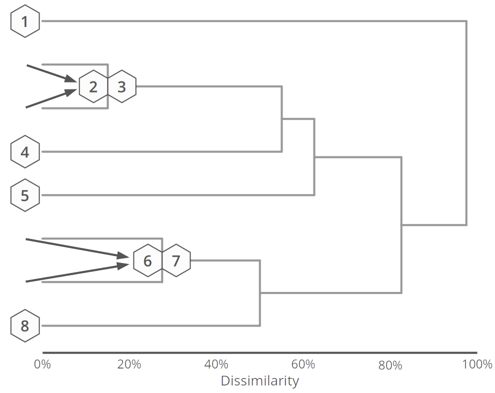
To get c clusters from ℓ, we create a list of node N, which we initiate to contain only ℓ_{root}. We then iteratively find the node in N with the maximum distance, remove it from N, and add its two child nodes to N. When $|N| = c$, N contains the c nodes that if completely unfolded (i.e. having their children recursively explored until all the leaf nodes are found), express the cluster information, which can be incorporated in T.

Relative Positioning

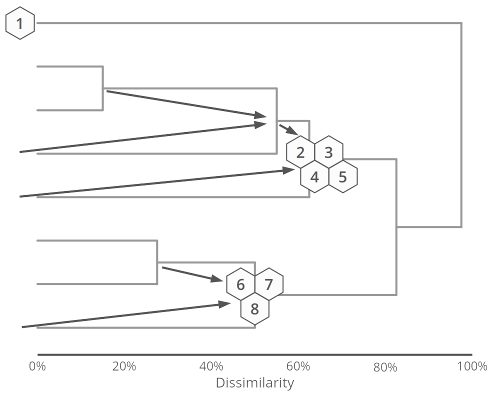
We developed this relative positioning algorithm to aggregate topics into a hexagonal map, depending on their relation in ℓ. We illustrate this process in Figure 3.10.



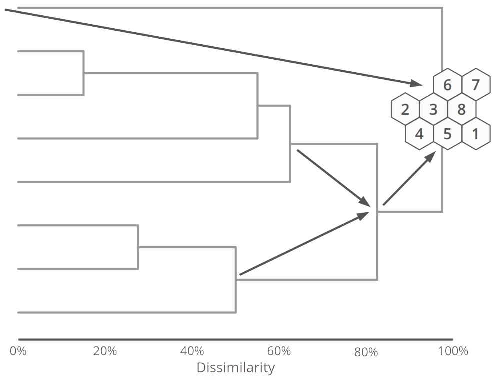
(a) The topics are first organised in a hierarchy using a linkage table (see previous section).



(b) The most similar topics (or least dissimilar) are put together first. In this case, topics 2 and 3, and then topics 6 and 7.



(c) The groups of topics are gradually merged, following the hierarchy previously defined.



(d) The same merging process is repeated until the complete Topic Map is formed.

Figure 3.10: Example of a relative positioning process using a linkage table, represented by a dendrogram (Figure 3.10a). Topics are gradually merged, started by the most similar first (Figure 3.10b), until the Topic Map is finished (Figures 3.10c and 3.10d).

We position a cluster of topics (represented by a linkage table node) in the map as follow, starting with ℓ_{root}:

1. If the node's descendants represent three or less leaf nodes we directly encode their coordinates so that they are neighbours of each other. The first leaf node

is the origin of that group.

2. Otherwise we recursively get the position of the node's two children clusters, and merge them into one.

Merging two clusters of hexagons, A and B, is done with the following process:

1. Get all the neighbour cells ${\eta^l}_A$ of A ($l = 1$ initially).
2. Compute all $B^{i,j}$, such that $B^{i,j} = \gamma(\rho(B, j), i)$, where:
   - $\rho(B, j)$ is the rotation of B of origin the origin of B and angle $\frac{\pi}{3}j$, with $0 \leq j < 6$.
   - $\gamma(B, i)$ is the translation of B to $i \in {\eta^l}_A$.
3. For all merging options $\{A, B^{i,j}\}$:
   (a) If $\{A, B^{i,j}\}$ presents overlapping hexagons, discard this merging option. If no options are found, restart from step 1 by incrementing l.
   (b) Otherwise compute the between-clusters weighted average Euclidean distance of $\{A, B^{i,j}\}$ (Equations (3.11) and (3.13)).
   (c) The option with the least distance average is chosen.

$$\bar{dist}_{eucl}(\{A, B^{i,j}\}) = \frac{\sum\limits_{t \in A, t' \in B^{i,j}} dist_{eucl}(t, t') D_{t,t'}}{\sum\limits_{t \in A, t' \in B^{i,j}} D_{t,t'}} \tag{3.13}$$

For this process, the positions are encoded in cubic coordinates to facilitate transformations. We convert those into two Cartesian dimensions, and incorporate the position information in T (see Appendix A, page 123).

3.4 Conclusion

In this chapter we presented the processes used to generated Topic Map data.

This data was generated from 14,083 textual research project descriptions. We retrieved those descriptions from a publicly accessible online portal (Section 3.1).

We then used a topic modelling application, based on latent Dirichlet allocation and collapsed Gibbs sampling, to extract topics from those project descriptions, or documents (Section 3.2). These topics are distributions of words, organised by their co-occurrences in documents. Based on the topics' proportions in the documents, we also calculate the dissimilarities between topics.

We finally mapped the topics onto hexagonal grids. Two layout mapping applications were used to that end, one implementing a reductive approach and the other a constructive approach (Section 3.3). Both of these mapping processes have two purposes: producing position information (mappable coordinates), and cluster information for the topics.

The projective mapping process (reductive) relies on making an estimation of the topics' positions, by embedding the topic dissimilarity information into two dimensions using Isomap. It then arranges the topics into a regular grid with the Hungarian algorithm. Topic clusters are computed using k-means.

The agglomerative mapping process (constructive) makes a hierarchical clustering of topics first, using the topic dissimilarity information. This hierarchy is then used to get the cluster information, but we also use it to position topics in relation to each other using an algorithm that we designed and implemented.

Each topic in the Topic Map data then comprises of three information:

- the topic labels (words with associated weights);
- the topic position (two-dimensional Cartesian coordinates);
- the topic cluster it belongs to.

This data constitutes the basis to create Topic Map visualisations. We make use of it in the next chapters, to generate Topic Maps and study user confidence in the visualisations and the processes used to create it.

Chapter 4

Study 1 - Explanation Systems and User Confidence

Our research goal is to increase the users' confidence in their ability to interpret and explain Topic Maps, and account for the decisions they lead to. Our proposed solution for this issue is to focus on the improvement of the Topic Maps interpretability. This chapter presents our first study on Topic Map interpretability and user confidence[1]. We refer to this study as *Study 1*.

For this research, we chose to expose the mapping processes to participants and investigate their responses. We design this exposure through Explanation Systems, which are presented in Section 4.1. Section 4.2 reports on a the pre-study work carried out, a numerical comparison of the accuracy of mapping processes and a pilot experiment.

We then introduce Study 1's research questions in Section 4.3. We report on our study design in Section 4.4 before detailing the experimental procedure in Section 4.5. We finally present the results of Study 1 in Section 4.6, discuss these results and their limitations in Section 4.7, and conclude this study in Section 4.8.

[1]The work presented in this chapter has been peer reviewed and published in the 2018 ACM Conference on Human Factors in Computing Systems (CHI) [66].

4.1 Explanation Systems

In the early stages of this research, we conducted to informal interviews with research managers to understand their potential use of Topic Maps. These managers are external to our university, and comprise one team working in a local institution and one individual working for a national organisation. We prompted the discussion by providing them a Topic Map generated using data from their respective organisations, and then talk through their impression and understanding of the Topic Map. Upon describing the rationale behind the placement of topics, they agreed that getting descriptions of the mapping process helped their interpretation and confidence.

These discussions were our main motivation to produce Explanation Systems[2], a type of application exposing the reasoning trace of mapping processes [44] that do not require the presence of an expert guiding non-technical users. The design of these Explanation Systems followed an iterative process of brainstorming prototypes within our research group.

In our final design, we set three essential requirements for Explanation Systems:

- To be **visual**, in order to display the reasoning trace without imposing the user to read text and transpose it to elements of the Topic Map visualisation [77].
- To incorporate **interactivity**, in order to give control to the user and allow them to navigate through the reasoning trace [52].
- To display **data-driven** content and make the Explanation System specific to the Topic Map users are working with, [44].

These requirements were formulated in order to reduce the cognitive efforts required from users, and facilitate the use of Explanation Systems. Similar guidelines have been suggested by Gregor and Benbasat for knowledge-based systems [44]. This study will evaluate whether these suggestions are valid for visualisation systems.

[2] In this thesis, the term *Explanation System* exclusively refers to an application exposing the reasoning trace of mapping processes.

Explanation Systems would expose the mapping processes to participants, which would allow us to gather information on their perception of the visualisation. We recognise however that showing only one type of Layout Method would introduce biases in the results. We therefore decided upon visualising two contrasting Layout Methods, to offer variety in the stimuli presented to participants and get more insights from them:

- one presenting a reductive approach: the Projective Method;
- one presenting a constructive approach: the Agglomerative Method.

In the following subsections, we detail our designs for the Explanation Systems of the two mapping processes, and the data needed to produce them.

4.1.1 Explaining the Projective Mapping Process

This Explanation System was designed to be agnostic and representative of any dimensionality reduction technique. As such, it does not show the computation of dimensions, as this step differs between techniques. Instead we focus on the reduction part, i.e. extracting the two most important dimensions from the multi-dimensional embedding.

To ensure the visual and data-driven requirements of the projective Explanation System, we saved two data structures from the mapping process (Section 3.3.1):

- the multi-dimensional embedding O of the dissimilarity information;
- the grid G, where topic points from the two-dimensional embedding P are mapped on to get the coordinates of each topic.

The projective Explanation System follows these steps:

1. Display the multidimensional data in a scatter plot matrix (Figure 4.1a). We chose this type of representation as it allows to show each layout resulting from the combination of any two dimensions in the dataset. Although the dimensions in O are ordered, we randomise them at this stage, to prevent users from thinking that the process simply removes the last dimensions. We

however ensure that the two final dimensions (in P) are in the correct order.

2. Allow the user a first action highlighting the dimension displaying the least variance of points (Figure 4.1b).
3. Allow a second action removing the highlighted dimension and rescaling the scatter plot matrix (Figure 4.1c).
4. Repeat step 2 and 3 until the final two-dimensional arrangement is found (Figure 4.1d).
5. Allow the user to map topic points to the grid one by one (Figure 4.1e).
6. When all points have been mapped, display the Topic Map (Figure 4.1f).

An example of the projective Explanation System at this address: strategicfutures.org/demos/TopicMappingExplanations/projective.html.

4.1.2 Explaining the Agglomerative Mapping Process

To meet the visual and data-driven requirements of the agglomerative Explanation System, we recorded the linkage table ℓ (Section 3.3.2). The agglomerative Explanation System follows these steps:

1. Display the topics in a vertical list, in dendrogram order (Figure 4.2a).
2. Allow a first action highlighting the most similar pair of topics, and their related dendrogram node (Figure 4.2b).
3. Allow a second action joining the topics, and moving them at the dendrogram node (Figure 4.2c). For the rest of the Explanation System, these topics will be considered as one unit.
4. Repeat step 2 and 3 until all topics have been joined (Figure 4.2d).
5. Display the Topic Map (Figure 4.2e).

An example of the agglomerative Explanation System at this address: strategicfutures.org/demos/TopicMappingExplanations/agglomerative.html.

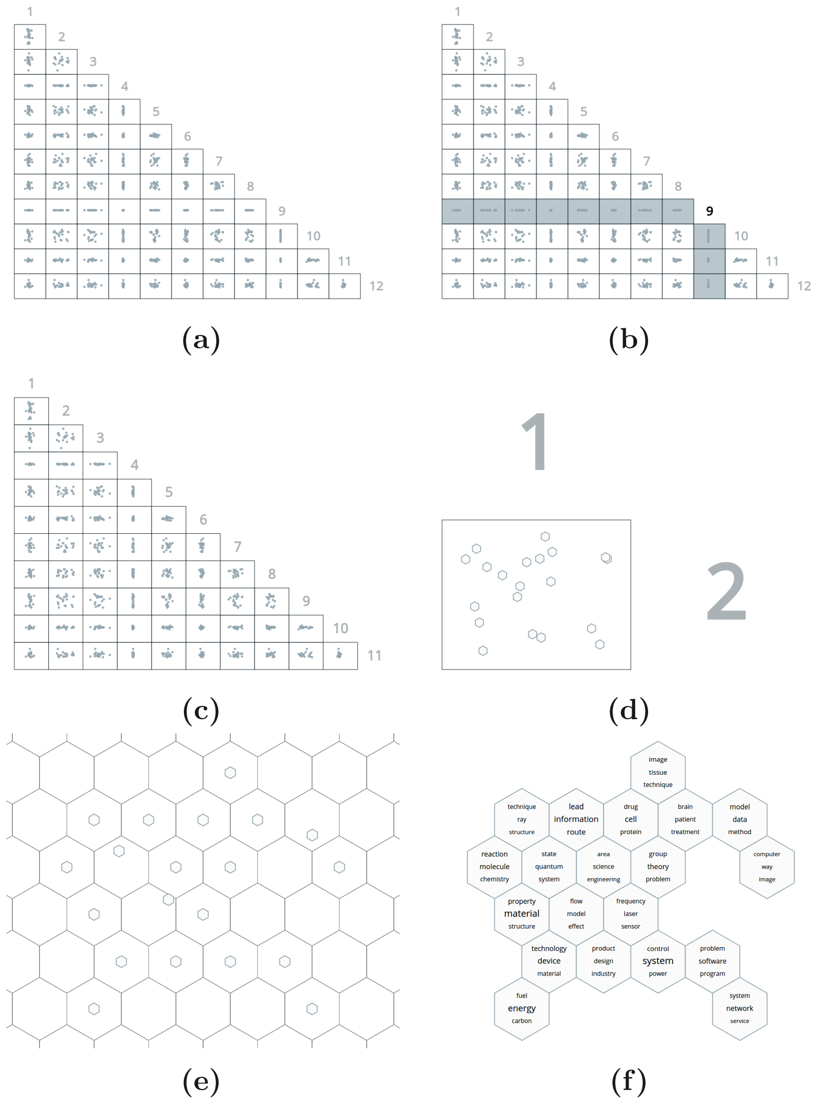


Figure 4.1: Explanation System for the projective mapping process. We first display the multidimensional data in a scatter plot matrix (Figure 4.1a). Users can then highlight and remove dimensions (Figures 4.1b and 4.1c), until two dimensions are left (Figure 4.1d). We then let the user assign topic points to grid cells (Figure 4.1e), until the Topic Map is complete (Figure 4.1f).

4.2 Pre-Study Work

4.2.1 Numerical Comparison of the Mapping Processes

In our study design we planned for participants to experiment with Topic Maps from both mapping processes. We therefore conducted a numerical analysis to ensure that participants could not discriminate between Topic Maps on the basis of their accuracy with respect to the underlying similarity information.

For each of 125 topic distance matrices, we generated two Topic Maps, one per

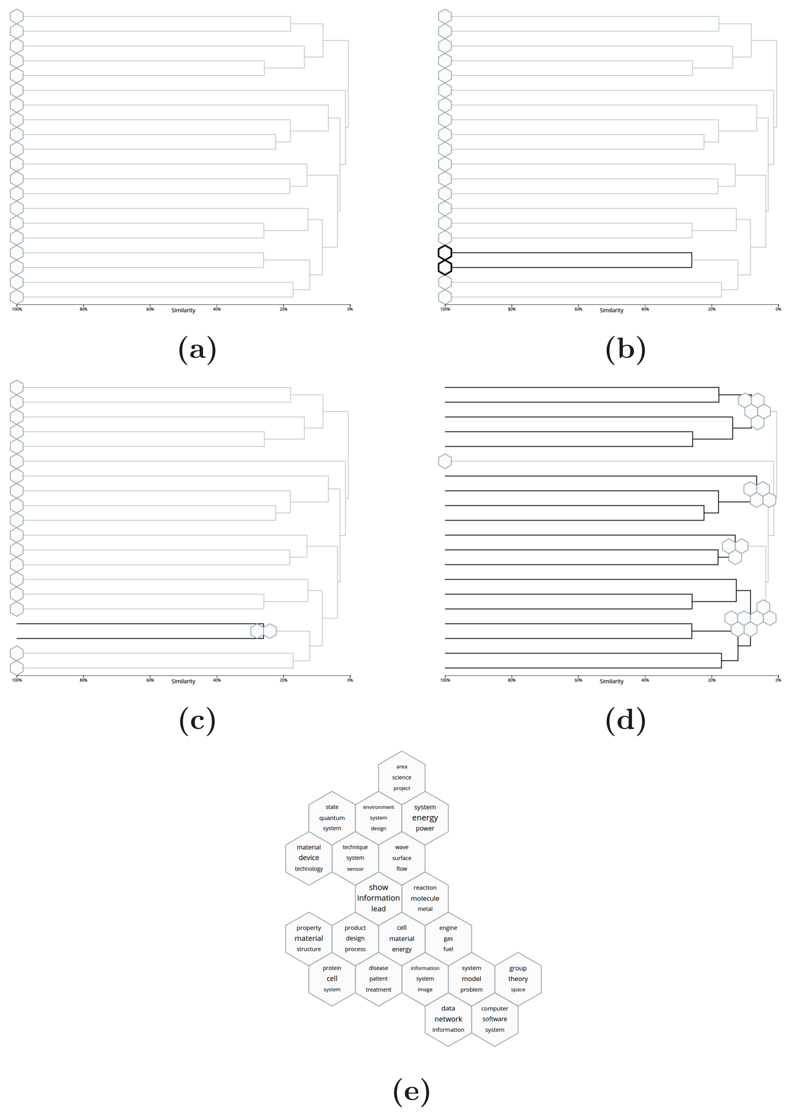


Figure 4.2: Explanation System of the agglomerative mapping process. The topics are initially shown in a vertical line, in dendrogram order (Figure 4.2a). Users can then highlight the most similar pair of topics (Figure 4.2b) and merge them (Figure 4.2c) at the dendrogram node where they join. We then let users iterate over the highlight and merge actions (Figure 4.2d), until the Topic Map is complete (Figure 4.2e).

mapping process. These topic distance matrices were created using random samples from our document pool. These samples had varying sizes, 100 to $3,000$ documents, as well as the matrices themselves, 10 to 50 topics.

We then computed the mean squared error of each Topic Maps against the distance matrix it represented. These measures are reported in Appendix C. An independent t-test revealed that, on average, the mean squared errors of the agglomerative Topic Maps ($M = 0.213$, $SE = 0.002$) were not significantly different from the mean squared erros of the projective Topic Maps ($M = 0.209$, $SE = 0.002$),

$t(248) = 1.171$, $p = 0.243$, $r = 0.074$.

This analysis showed that there is no significant difference in the validity (or fitness) when measured numerically, of the two mapping processes.

4.2.2 Pilot Experiment

Before conducting the main study, we decided to conduct a pilot experiment to test the feasibility and efficiency of a task-driven repeated-measure of confidence using Likert scales.

This pilot experiment tasked the participant with interacting with both of the Explanation Systems and understand the relative placement of two highlighted topics. This task was repeated 20 times, and the participant had to report on their confidence of interpretation and ability to explain using an 11 points Likert scale after each completion. This scale ranged from 0% (*no confidence*) to 100% (*strong confidence*) using 10% increments. A follow-up interview was also conducted.

This pilot experiment confirmed that the Explanation Systems work as applications. The quantitative nature of this experiment design however did not allow us to gather meaningful insights from the participant. In particular, the participant expressed difficulties in quantifying their confidence rating, as well as fatigue from the task repetition. In comparison, we gathered valuable in-depth comments from the participant during the follow-up interview.

We therefore decided upon changing our study design towards qualitative methods, using semi-structured in-depth interviews [2].

4.3 Research Questions and Hypotheses

The aim of Study 1 is to investigate the use of Explanation Systems to improve the users' confidence in their ability to explain Topic Maps. We focus this investigation on two research questions.

RQ1.1: *What are the overall effects of Explanation Systems on user confidence?*

We hypothesise that Explanation Systems propose two advantages. First they give the user the opportunity to witness the algorithmic decisions made by a layout mapping application. And second, they let them control the rate at which they get the information. We think that the combination of those two factors would increase the interpretability of the Topic Map and the users' confidence in their ability to explain it.

RQ1.2: *What are the specific effects of each Layout Method on user confidence?*

As we are exposing two mapping processes, we are expecting differences in the user confidence. We think that the Agglomerative Method presents processes that would fit the users' mental model better. Conversely, we believe that the multi-dimensional aspect of the Projective Method would be more confusing to the users.

4.4 Study Design

4.4.1 Interviews

To explore our hypotheses, we decided to conduct semi-structured scenario-based interviews. Using semi-structure interviews allows for unexpected participant views to be pursued as they arise and when appropriate [2]. In addition, the use of a scenario allows to focus and contextualise the participants' opinions [10, 55]. In particular, given that our participants would be recruited within our university department, we incorporated research and courses into the scenario to help them connect with it and bring intrinsic and empathic motivations [11].

After being introduced to topics, Topic Map visualisations, and the instructions for the interview, the participant would be presented with the scenario in which they had to place themselves:

"The university commissioned us to create overviews of topics in order to facilitate a possible reorganisation of research groups, by merging or splitting them. The data used for those maps was provided by the UK research councils. The reorganisation could affect Ph.D. or fellowship allocations and maybe the courses taught. Once the decisions are made your role is to announce them to affected groups."

We then divided the interview in three phases (Phase 1, Phase 2, and Phase 3), all following this pattern:

1. Present the participant with a Topic Map application.
2. Point out conflicting topic positions to the participant, e.g. when two topics are neighbours while a separated third on should have been closer, suggesting an unusual merging or splitting of research areas.
3. Invite the participant to interact with the Topic Map and Explanation System views (when applicable).
4. Conduct part of the interview with the participant, allowing them to access the view(s) to facilitate the discussion.

In Phase 1, the participant would only be presented with a Topic Map, i.e. without an Explanation System, using either mapping process. The discussion would start in the context of the scenario, before probing the participant on their confidence (Figure 4.3).

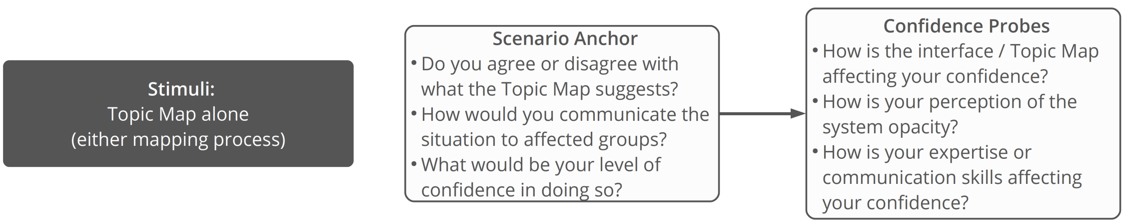


Figure 4.3: Example questions for Phase 1. For this phase, the participant is presented with a Topic Map alone, generated using either mapping process. The questions would start in the context of the scenario before probing participants' confidence. This configuration could however be affected by the semi-structured nature of the interview.

In Phase 2, the participant would be presented with a Topic Map and the associated Explanation System, using either mapping process. As with Phase 1, the discussion would start in the context of the scenario, using a similar set of questions.

The discussion would then query the participant on their confidence using the Explanation System. To probe this aspect further, the participant was asked about the Explanation System usability (difficulty or ease of use, length, engagement, potential reuse) and deeper themes: the data-driven and interactive nature of the Explanation System, their perception of the Topic Map after seeing the Explanation System, and the use of the Explanation System in the scenario (Figure 4.4).

Contrasting the participants' comments between Phase 1 and Phase 2 would aim at exploring **RQ1.1**.

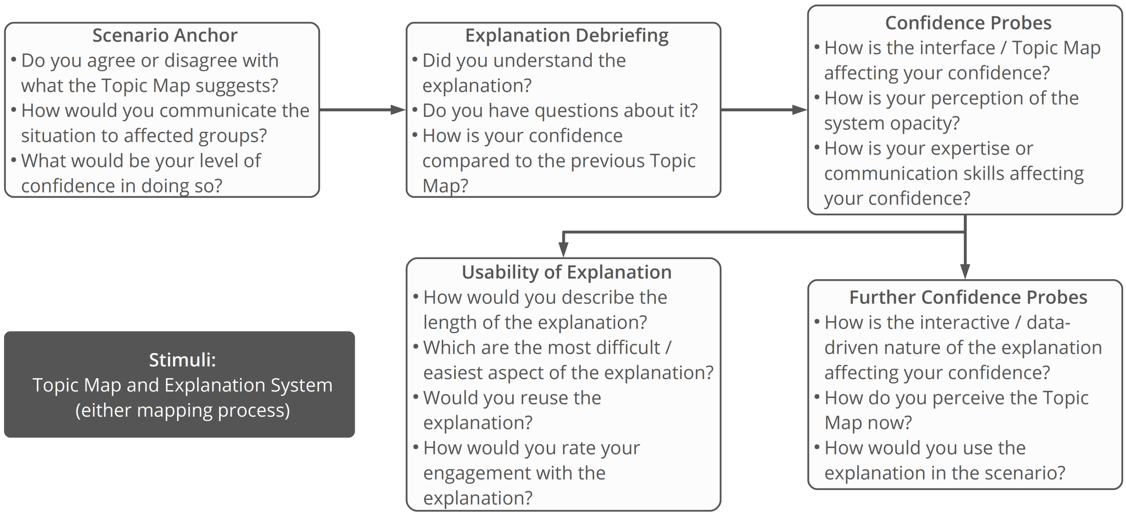


Figure 4.4: Example questions for Phase 2. For this phase, the participant is presented with a Topic Map and the associated Explanation System, generated using either mapping process. The questions would again start in the context of the scenario before probing the participant's confidence in using the Explanation System, while contrasting it with their impressions from Phase 1. Similar to Phase 1, this configuration could be affected by the semi-structured nature of the interview.

In Phase 3, the participant would be presented with a Topic Map and the associated Explanation System, using the other Layout Method than with Phase 2. The discussion in this phase would start by making the participant reflect on their understanding of the Explanation System, to then query their contrasts between the two Layout Methods (Figure 4.5).

Contrasting the participants' comments between Phase 2 and Phase 3 would aim at exploring **RQ1.2**.

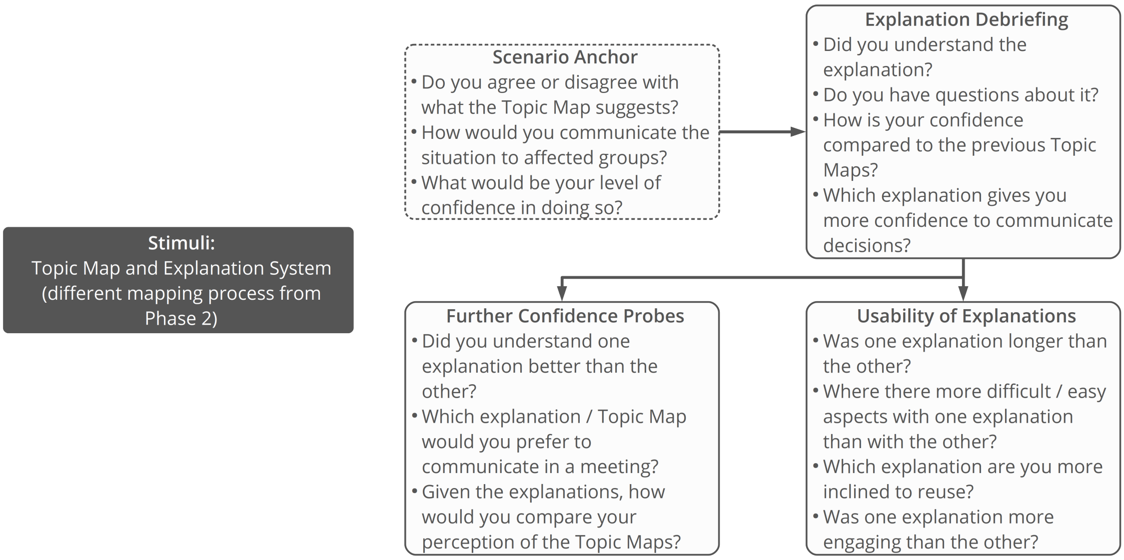


Figure 4.5: Example questions for Phase 3. For this phase, the participant is presented with a Topic Map and the associated Explanation System, generated using the alternative mapping process than with Phase 2. When time allowed it, the questions would start in the context of the scenario. This interview phase would mostly revolve around contrasting the participant's perception of the two Layout Methods. Similar to Phases 1 and 2, this configuration could be affected by the semi-structured nature of the interview.

4.4.2 Stimuli

For this study, we developed a web application that presents the participant with a series of views. Two types of views were implemented: a Topic Map view, and an Explanation System view.

Although our pilot experiment displayed clusters in the Topic Map and Explanation System views (using coloured hexagons), we noticed that it distracted our participant's comprehension of the mapping processes. Since the Explanation Systems are not purposed for explaining cluster estimation, we decided upon eliminating this cofounding factor in this study.

The Topic Map view presents a Topic Map on the left-hand side (Figure 4.6). When the user selects a topic in the Topic Map, the right-hand side of the view shows a wordcloud of the full topic, and a table of the top ten similar topics. The wordcloud would enable a better understanding of the nature of a topic. Including a list of similar topics aimed at accentuating contentious placements. We emphasized this aspect by enabling highlight interactions between the Topic Map and the list.

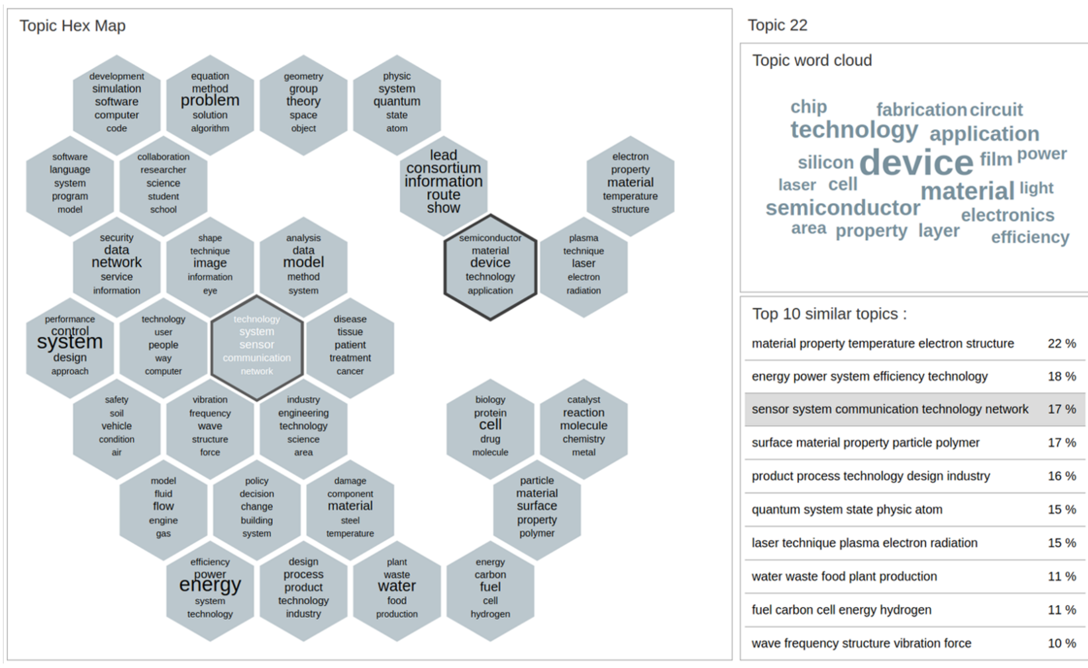


Figure 4.6: Topic Map view presented in Study 1. The left-hand side presents the Topic Map. The right-hand is fully displayed after the participant selects a topic, and shows a complete wordcloud of the topic labels, and a list of the ten most similar topics.

The Explanation System view presents the Explanation System on the left-hand side (Figure 4.7). As per our interactivity requirement for Explanation Systems, the right-hand side of the view shows buttons that allow the participant to proceed through the Explanation System step-by-step, fast-forward, or back-track. A short description accompanying these controls would describe the current state of the mapping process.

In addition to the stepping controls, we added interactions between the Explanation System and a minified Topic Map on the right-hand side of the view:

- Hovering over a topic displays the topic's labels in a tooltip, while highlighting the topic across the view.
- Clicking on a topic places a permanent marker on it (in black).
- A second click changes the marker color to white, allowing for the participant to track two groups of topics.
- A third click removes the marker.

The purpose of these interactions is to allow a quick identification and tracking of topics throughout the Explanation System, in order to aid the participant in their task, i.e. understanding the relative placement of topics.

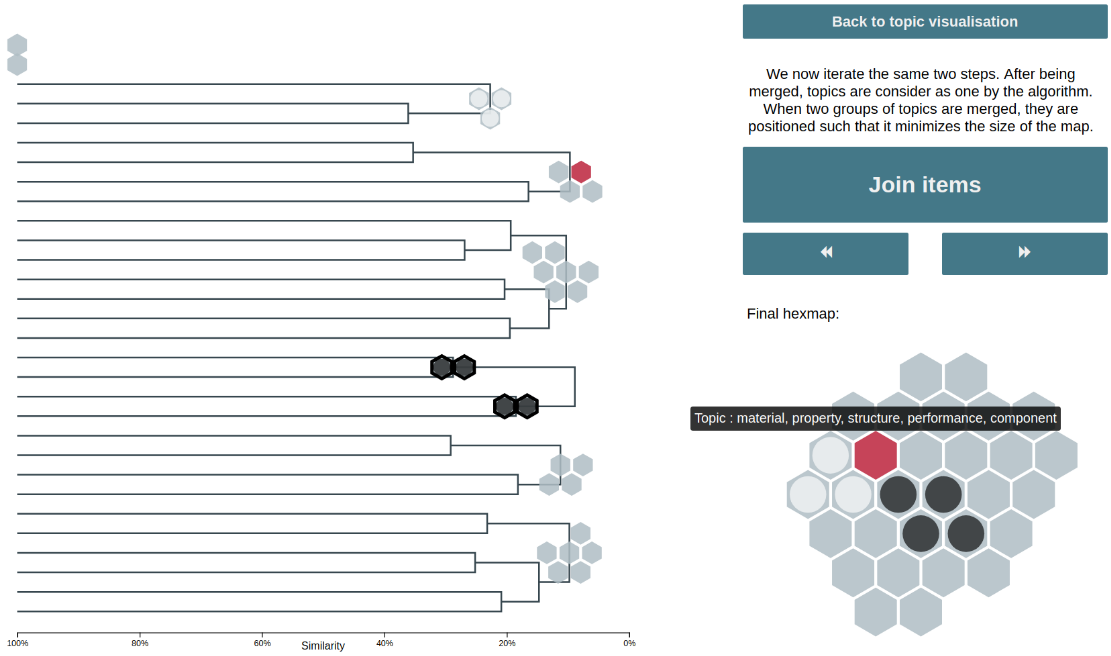


Figure 4.7: Explanation System view presented in Study 1. The left-hand side shows the Explanation System of a specific Topic Map. The right-hand presents the Explanation System stepping controls, and a minified Topic Map. Interactions include: highlight upon hovering, and marking upon clicking. This figure illustrates the Agglomerative Method, however, both Layout Methods use the same Explanation System view.

The flow between the views is as described by the interview design (Figure 4.8): Phase 1 only presents a Topic Map view (from either mapping process); Phase 2 shows a Topic Map view (from either mapping process) from which the participant can access the Explanation System view using a link; Phase 3 behaves similar to Phase 2, but changes the Layout Method.

Two topic models where made to generate the Topic Maps. Both of them comprised of 30 topics, and used different subsets of 7,000 documents each to ensure that the resulting Topic Maps would be different. The Topic Maps generated from the first topic model were used in Phase 1. The Topic Maps generated from the second topic model were used in Phase 2 and 3.

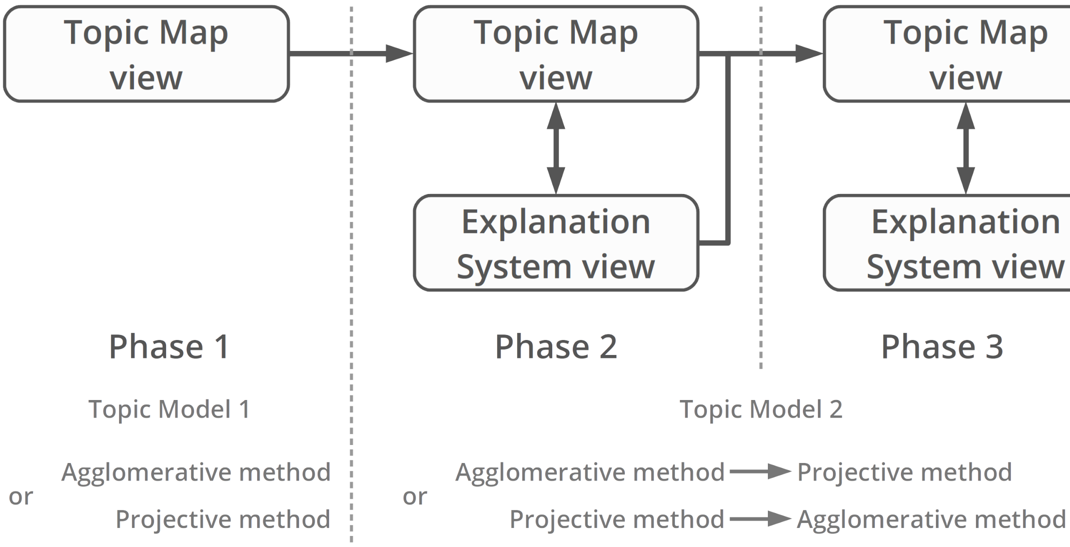


Figure 4.8: Flowchart of the stimuli organisation. Phase 1 only comprises of a Topic Map view, while Phase 2 and Phase 3 have an Explanation System view available. The topic model used to create the Topic Map changes between Phase 1 and Phase 2. Besides balancing the stimuli across participants, the only requirement for the choice of mapping process is that Phase 3 presents the alternative to Phase 2.

4.5 Procedure

We conducted the study with 10 participants (P1.1 to P1.10), recruited using convenience sampling within our university department, in order to get a pool of participants with scientific or engineering backgrounds, and therefore familiar with the data presented (scientific and engineering research grants). The following demographic and experience information was recorded:

- age (optional);
- occupation (optional);
- frequency of use of static visualisations on a 7 points Likert scale;
- frequency of use of dynamic visualisations on a 7 points Likert scale;
- frequency of visualisation creation on a 7 points Likert scale.

We gives details on the participants' background for this study in Appendix D, page 129. The participants' demographics show an age range from 21 to 38 ($M = 27.1$, $SD = 6.1$), and a cohort of 2 undergraduate, 2 postgraduate, and 4 research students, and 2 researchers. There was a range of experience background, but none of the participants reported to be an expert in data visualisation. This fits the knowledgeable but non-technical user profile that we are targeting.

We were granted ethical approval for this study, and all participants completed a consent form (Appendix B, page 126). All the recorded data was anonymised and unlinked. Each participant was rewarded with a £10 Amazon voucher for their participation.

We distributed the stimuli across the participants in order to balance the mapping process presented in Phase 1, and in Phase 2 (and thus Phase 3).

The interviews length varied between 25 and 40 minutes. The stimuli were presented in a controlled environment for all participants. We used a 24 inches monitor with a 1920*1080 pixels resolution. The monitor was color-calibrated to ensure a consistent display of the views for all participants. Each interview was audio taped, before being transcribed.

The transcripts were analysed by two coders, using NVivo, a Computer-Assisted Qualitative Data Analysis Software (CAQDAS) [73]. It facilitated the categorisation and count of comments, and the computation of the Intercoder Reliability (ICR) [99]. The codebook development was done with an inductive approach and using coding calibration [28]. First the coders randomly selected two transcripts and agreed on an initial codebook that would reflect the interview structure and common points observed. They then coded one interview and met to discuss limitations and disagreements, before refining the codebook unitisation and organisation. The transcripts were then coded using an open-coding approach, and a second pass through the interviews ensured consistent coding.

The ICR was calculated using Cohen's Kappa (κ) [19]. Cohen's Kappa evaluates the coders' agreement measure while taking into account the chance of random agreement. The ICR evaluation revealed a κ of 0.54 with an agreement of 88.56% across all codes and transcripts. We argue that these figures reflect two aspects:

- The codebook is meaningful, and allows a relatively objective coding.
- The codebook is however not too restrictive, and allows subjectivity in the

interpretations, which maximises comment coverage in later analyses.

The final codebook comprises six key categories:

- *Topic Map*, for comments relative to the Topic Maps alone;
- *Explanation System*, for comments relative to the Explanation Systems;
- *Agglomerative Method*, for comments relative to the Agglomerative Method and associated Topic Maps;
- *Projective Method*, for comments relative to the Projective Method and associated Topic Maps;
- *Confidence*, for comments relative to the participants' confidence in interpreting and explaining the Topic Map or the Layout Method;
- *Usability*, for comments relative to usability of the Topic Map and the Explanation System.

These categories also include subcategories that reflect positive or negative comments. Finally, other categories, such as *Personal reasoning*, *Scenario reasoning*, *Suggestions*, *Questions*, and codes for the three phases of the interviews, contributed to a better understanding of the results.

4.6 Results

4.6.1 Overview of Interviews

Table 4.1 presents the counts and proportion of sentiment for each of the six key categories identified during the coding process. We acknowledge that part of these results have been influenced by the interview structure, we however argue that we can extract insights from those numbers. First, looking at the proportions between Topic Map and Explanation System codes, positive comments rose from 21% to 58%. We think this highlights the improvement in user confidence when our participants were exposed to the Explanation Systems.

Secondly, we notice that participants were more positive about the Agglomer-

	Topic Map	Explanation System	Agglomerative Method	Projective Method	Confidence	Usability
Positive	36	231	162	52	154	46
	21%	**58%**	**55%**	**22%**	51%	57%
Neutral	100	129	96	113	109	23
	59%	33%	33%	47%	36%	28%
Negative	34	36	36	73	40	12
	20%	9%	**12%**	**31%**	13%	15%
Total	170	396	294	238	303	**81**

Table 4.1: Study 1 Coding: counts and proportions of positive, neutral, and negative sentiments for each of the six categories identified by the two coders in the coding process.

ative Method (55%) than with the Projective Method (22%). Likewise, the participants were more negative towards the Projective Method (31%) than towards the Agglomerative Method (12%). These contrasts are even more striking when considering that both Layout Methods were mentioned with a similar order of magnitude in total. These figures lead us to note a preference towards the Agglomerative Method from our participants.

Finally, although our study design focused on user confidence (which is reflected in the total counts of Confidence comments: 303), we wanted to account for usability factors. Our results, however, show that in general participants did not expand on Usability (81 total counts). We believe this means that the usability of the Topic Map and of the Explanation System did not impact the result we gathered about user confidence.

These results only present an overview of the interviews. We present more in-depth insights in the following two sections.

(a)	"This interface will give me more confidence, for areas that I do not know much about." (P1.1)
(b)	"I think by showing them the visualisation, and show the more relation they have to this field, I would be confident to support my opinion." (P1.4)
(c)	"I am just basing my confidence on what I am seeing. And actually what I am seeing is not so encouraging to have like a 60 or 70 percent confidence [...] to defend my point." (P1.6)
(d)	"Directly like that, it would not be too clear to me how [the Topic Map] was constructed. [...] there needs to be a stronger relation to the underlying data." (P1.5)
(e)	"I think it would be useful to have some sort of secondary explanation on top of that because [...] people that are external from various sections displayed here would find it difficult to find the correlation." (P1.7)

Table 4.2: Participants' quotes about Topic Maps without Explanation Systems. Despite acknowledging a good confidence in using the Topic Map, participants expressed a need for more explanation.

4.6.2 Overall Effects of Explanation Systems

In this section we contrast the participants' comments between Phase 1 and Phase 2 of the interviews. This analysis explores RQ1.1: *What are the overall effects of Explanation Systems on user confidence?*

User Confidence Without Explanation Systems

During Phase 1, four of the ten participants expressed a positive confidence towards the Topic Maps. Specifically, they commented that it enabled them to reinforce their knowledge, and their views on a situation (Table 4.2a and 4.2b).

Nine of our participants however commented that a Topic Map alone was not enough to confidently interpret or explain the layout mapping and the decisions it may lead to, Table 4.2c is an example. This issue is the same professional research managers reported to us during informal interviews. In particular, participants reported a need for data-based evidence and explanation (Table 4.2d and 4.2e).

The Topic Maps were recognised by some participants to be a good tool for decision making activity. The majority (nine out of ten) however explicitly reported that it was not enough, and expressed their uncertainty about their task within the scenario. Mainly, the participants thought that their confidence would increase given more evidence and explanation about the Topic Map. We believe this reinforces the need for Explanation Systems and highlights their positive influence on user confidence.

User Confidence with Explanation Systems

During Phase 2 of the interviews, the participants interacted with the Explanation Systems. With both Layout Methods, we observed an increase in the participants' confidence. We have divided this analysis into three parts: evidence, interactivity, and adoptability.

Evidence: When exposed to Explanation Systems, a majority of our participants (eight out of ten) plainly indicated having a stronger confidence in being able to interpret and explain a Topic Map to others (for example Table 4.3a and 4.3b). In addition to the decisions they had to report in the scenario, the participants also commented that the Topic Map overall appeared more robust (Table 4.3c and 4.3d).

In Table 4.3e, P1.5 points out that the Explanation System provides more evidence than Topic Maps alone. This opinion was shared by eight of our ten participants, and three directly related it to an increase of confidence in their ability to make and explain decisions, Table 4.3f to 4.3h show examples of such statements.

An Explanation System particular to the underlying data of a Topic Map: *a*) increases the participants' perception of robustness of the Topic Map, *b*) extends the participants' understanding of the Topic Map organisation, and finally *c*) improves the participants' confidence in their ability to explain to others the mapping process, and decisions made based on the Topic Map.

Interactivity: For our participants, the interactivity of the Explanation Systems allowed greater control over them, improving their confidence, and brought more

(a)	"Knowing how this [Topic Map] is constructed, I am more confident that the splitting and merging [...] make sense to me." (P1.5)
(b)	"Now you know what you are saying and why you are going to say it. It does help to know." (P1.6)
(c)	"[The Topic Map] is more realistic, actually." (P1.6)
(d)	"The [Explanation System] is like a bonus, to trust the map more [...], it is better than the map by itself." (P1.8)
(e)	"[The Explanation System] gives me a second level of information, which the Topic Map by itself lacks, so I can see all those similarity values [...] which I cannot see from the Topic Map itself." (P1.5)
(f)	"The [Explanation System] gives me a good view of how the system works and how, for example, the merging or the breaking [of areas] is succeeded." (P1.4)
(g)	"[In] the previous [Topic Map], I was just blind and I made my decision based on my feelings rather than knowing what I am doing, but here I did have some material to base my decision on." (P1.6)
(h)	"It makes it a lot clearer, how the decisions are founded because A and B are connected, and C and D are kind of neighbouring. [...] I would give you more confidence in decisions that are made [...] if it was backed with like hard evidence there." (P1.7)

Table 4.3: Participants' quotes about the evidence that Explanation Systems provide. Incorporating Explanation Systems with Topic Maps enabled participants to get an increase in confidence, both regarding the Topic Map and their ability to explain it.

engagement (Table 4.4a). This included the data-driven aspect as well. Eight participants said it made the Explanation System more meaningful, for example Table 4.4b and 4.4c.

Incorporating interactivity in Explanation Systems increased the participants' confidence and engagement as it enabled them to query individual items, have control over the step-by-step process, and understand the information at their own pace. This increase is particularly pronounced when the participants contrasted them with the use of non-interactive media, such as video tutorials.

Adoptability: Seven of our ten participants explicitly expressed their willingness to reuse Explanation Systems, which attests to a stronger confidence. P1.4, P1.5,

(a)	"It is definitely good to have the [Explanation System] where you can pause, play back and play forward, so that I can actually pause at points that I might be interested in. I mean if I really would have to decide something, then I personally would really interested to see that visually and to find things where I have to argue, and to see them kind of over time." (P1.5)
(b)	"It is better to have [an Explanation System] that is related to the data in real time. [...] A video is just taking time and it does not change if we have to change the data. [...] I would be more confident to have [an Explanation System] that is directly related to the data." (P1.8)
(c)	"I think it is better to have it showing why it came to this specific example rather than generic one. [...] I think it is probably better just to show all the steps and explain along the way why it took those steps." (P1.10)

Table 4.4: Participants' quotes about Explanation Systems' interactivity. Making Explanation Systems interactive allowed our participants to have control over it. With the data-driven aspect, it made the Explanation Systems more meaningful.

(a)	"I have a strong explanation of how the results were produced and by explaining to everyone, [...] I think no one could [...] argue." (P1.4)
(b)	"If [...] you can show the explanation, then I think it is easier to convince people that this is correct. Without the explanation [...] it might not be that clear to people how this map was generated." (P1.5)
(c)	"I think it would resonate more with people, having this kind of [Explanation System], kind of hard evidence [...] when someone is talking to you about something, I do not think it does ring as true as kind of having it shown right in front of you." (P1.7)

Table 4.5: Participants' quotes about the adoptability of Explanation Systems. The evidence brought by Explanation Systems gave them the confidence to convince others.

and P1.7 indicate this willingness (Table 4.5a to 4.5c), and link it to the evidence displayed by Explanation Systems.

The evidence and interaction provided by the Explanation Systems gave our participants the confidence to explain, argue, convince, and present Topic Maps in detail. As such, they exhibited eagerness to adopt and make repeated use of Explanation Systems.

4.6.3 Specific Effects of Each Explanation Systems

In this section we contrast the participants' comments between Phase 2 and Phase 3 of the interviews. This analysis explores RQ1.2: *What are the specific effects of each Layout Methods on user confidence?*

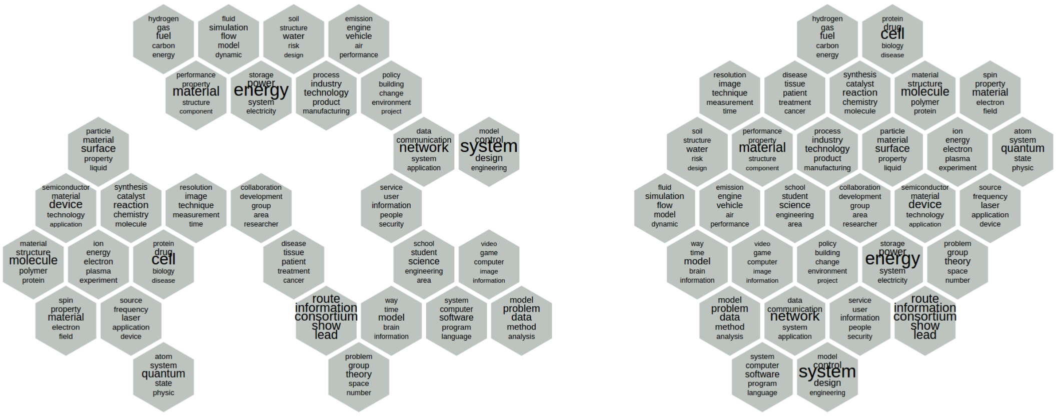
In our hypotheses we mainly considered algorithmic interpretability. Our results however revealed that the participants also valued credibility as part of it. Both of the Layout Methods where found interpretable and credible, each for different reasons however. The next sections detail those reasons. First, the Topic Map layout itself emerged as being important, notably with its density. Secondly, the mapping process, represented by an Explanation System, was also significant, the clarity of it being the main factor.

Topic Map Layout Density

The Projective Method design aims at maintaining the most distance between topics. As such, it produces Topic Map layouts that spread the topics (Figure 4.9a). This low density of topics made the Topic Map, and the Projective Method, more credible, and improved the confidence of our participants, as expressed by P1.5 and P1.6 (Table 4.6a and 4.6b).

In contrast, the Agglomerative Method aggregates the most similar topic cluster recursively and creates dense Topic Map layouts (Figure 4.9b). While this allows the closest topics to become neighbours in the Topic Map, it does not account for more distant clusters later in the process, P1.8 describes this and how it affects their perception of the Topic Map (Table 4.6c).

The density of the Topic Map layout plays an important role in the credibility and interpretability of both the Topic Map layout and the Layout Method. While dense layouts provide a better display utilisation, sparser layouts make the relationships between items more obvious and meaningful, thus increasing our participants' confidence. Moreover, the aggregation process presented by the Agglomerative Method,



(a) Projective Topic Map layout **(b)** Agglomerative Topic Map layout

Figure 4.9: Example of a projective Topic Map layout (Figure 4.9a) and an agglomerative Topic Map layout (Figure 4.9b). These two Topic Maps were used in Phase 2 and 3 of the study and were generated from the same topic model. The difference of density affected the credibility of the Topic Maps for the participants.

(a)	"[The projective Topic Map layout] seems to be more in line with what I would expect, because you actually do not have a dense map, so you have missing grid lines in between which would translate to me into having bigger distances. So the [projective Topic Map layout] actually includes the notion of distance between topics, better that the [agglomerative] one." (P1.5)
(b)	"This [agglomerative Topic Map layout] is quite dense, [. . .] I think the [projective] one is more specific than the [agglomerative] one." (P1.6)
(c)	"At the beginning [. . .] all the topics that are together are really [together], we can understand that they are related together. But at one time [. . .] we force them together even if they do not have any links. [. . .] it feels unnatural." (P1.8)

Table 4.6: Participants' quotes about the density of Topic Map layouts. The participants expressed a preference towards the projective Topic Map layout as it spreads the topics more than the agglomerative Topic Map layout.

although efficient and meaningful at the beginning, eventually appears to *force* clusters together, thus decreasing the participants' confidence.

Layout Method Clarity

The Agglomerative Method presents however an advantage to our participants: its clarity (Table 4.7a and 4.7b). In comparison, the Projective Method appeared confusing (Table 4.7c). The participants justify these impressions by the fact that the

(a)	"Just looking at the explanation that you provided, I would say that the [Agglomerative Method] gives me a clearer view of how the topics are related to each other, and how the process is done." (P1.4)
(b)	"I understand the way [Agglomerative Method] works more, [...] merging them together one by one, by the most similarity first [...]. I think that makes better sense [...] that the [Projective Method]." (P1.10)
(c)	"To be honest, I am a bit confused by the [Projective Method]." (P1.9)
(d)	"It resounded more to me. [...] It was just the clearest [...]. It visually made more sense." (P1.7)
(e)	"I found the [Agglomerative Method] shows the clustering more naturally as how I think. And [the Projective Method], I have too many questions and too many things I need to understand first before I can fully understand [...] why this is presented this way." (P1.9)
(f)	"In the [Projective Method] [...] you found [dimensions] and they disappeared, and then nothing really [...]. Whereas in [the Agglomerative Method] [...] [the topics] merged together and kind of took their own shape. [...] You can understand a bit more how those topics were in relation to each other." (P1.10)

Table 4.7: Participants' quotes about the clarity of Layout Methods and the participants' mental model. The Agglomerative Method presented an approach that suited our participants' mental model, while the Projective Method appeared confusing.

Agglomerative Method is more in line with their mental model, while the Projective Method requires prior knowledge, as P1.7, P1.9, and P1.10 explain in Table 4.7d to 4.7f.

The Agglomerative Method was found by nine participants to be more interpretable. This was reflected by the number of participants to which the Projective Method had to be clarified (seven) in comparison to the Agglomerative Method (one). When talking about interpretability, the participants both used a personal perspective, like P1.8 (Table 4.8a), and spoke within the scenario (Table 4.8b to 4.8d).

This preference extended to the participants confidence in explaining the Layout Method, and the decisions made from the Topic Map. All participants found the Agglomerative Method easier to explain (for example Table 4.8e to 4.8g).

(a)	"I did understand [the Agglomerative Method] better than the [Projective Method]." (P1.8)
(b)	"[The Agglomerative Method] requires less explanation perhaps [...]. This is easier for a more generic audience to follow." (P1.2)
(c)	"I think in terms of explanation for the audience [the Agglomerative Method] would be more understandable to people." (P1.4)
(d)	"The [Projective Method] is a bit complex. [...] [The Agglomerative Method] should be accessible to everybody." (P1.6)
(e)	"I feel like I would not be able to explain [the Projective Method] myself." (P1.1)
(f)	"Definitely [the Agglomerative Method] would be easier to explain." (P1.8)
(g)	"I think if you feel more confident in the system, you are going to be more confident with the decision or communicating the decision. [...] I would find [the Agglomerative Method] more useful." (P1.7)

Table 4.8: Participants' quotes about interpretability and explainability of Layout Methods. The Agglomerative Method appeared to our participants to be more interpretable and explainable than the Projective Method.

In contrasts with the Projective Method, our participants found the Agglomerative Method clearer to interpret and considered it a more natural process. The gradual presentation and aggregation of topics helped build the process credibility and interpretability, and increased the participants confidence in explaining the Topic Map layout. Conversely, the elimination process presented in the Projective Method displayed multiple structures before discarding them, and made the process less engaging for our participants. In addition, the unfamiliarity of our participants with notions such as *multi-dimensional* data, made the Projective Method confusing for them.

Eight of our ten participants stated they had more confidence when using the Agglomerative Method than with the Projective Method. Similarly, six participants explicitly claimed they would reuse the Agglomerative Method in preference to the Projective Method.

4.7 Discussion

One of the goal of this study was to study the effects of Explanation Systems, as well as the validity of our requirements for such systems (visual, interactive, data-driven). In light of our results, we believe in their suitability as a medium for communicating processes such as layout mapping, and encourage the community to extend their use to other visualisation, Machine Learning, or Artificial Intelligence methods. Such efforts have been produced in the recent Visualization for AI Explainability workshop [27].

This study however presents limitations. Mainly, despite the scenario we set out for them, our participants' answers remain hypothetical. An ideal study design would see the participants having to present the Layout Methods to another naive participant, or better an audience. Data could then be gathered from the active participant, on their actual experience, and from the passive participant(s) on their understanding of the presentation. How ever desirable are these experimental setup, pragmatic constraints did not allow us to address them.

Another limitation resides in the scope of this study. Although we aimed at providing sufficient contrasts between the two Layout Methods, the study design did not allow us to pursue the participants' views with enough depth. As such, the next chapters (Chapters 5 and 6) will present follow-up studies based on the results of Study 1.

In this study, we categorise a statement "confidence-related" if it was within context explicitly about confidence, whether it started with a question from the interviewer, or a comment made by a participant. By analysing and discussing the vocabulary used by participants in these contexts, we establish the following guidelines to assess whether a participant conveys notions of confidence in their statements:

- confidence vocabulary, e.g. "I would be more confident", "I do not think I would trust";

- preference for something when asked to perform a task, e.g. "I would prefer to use this", "I would choose this instead of that";
- ease or difficulty report, e.g. "This is easy", "It is too complicated", "I cannot do that";
- complexity or clarity rating, e.g. "This is confusing", "This is simple", "It is not clear".

Establishing such guidelines allows us to better analyse results of latter studies with regard to user confidence.

4.8 Conclusion

In this study we explored user confidence in the layout mapping of Topic Maps.

Our approach was to expose the mapping process through a Explanation System application that displays the algorithm in a visual, interactive, and data-driven manner (Section 4.1). We did so for two Layout Methods, to ensure a diversity of stimuli.

After attempting a mixed method pilot experiment (Section 4.2), we decided upon conducting a qualitative study, using semi-structured interviews. In particular we aimed at answering two research questions (Section 4.3):

- ***RQ1.1****: What are the overall effects of Explanation Systems on user confidence?*
- ***RQ1.2****: What are the specific effects of each Layout Methods on user confidence?*

The interview structure, and stimuli information are detailed in Section 4.4, and we present our procedure in Section 4.5.

Our results (Section 4.6) show that Explanation Systems increased user confidence. Notably by bringing evidence for decision making activities, and giving interactivity to allow users to explore and query the mapping process at their own space.

We therefore recommend that designers consider this type of application to provide users with the necessary confidence to use their visualisations.

We also found that visually displaying algorithms to users allows them to form deeper criticisms. As it would allow a visualisation designer to effectively rethink the data transformation process, it gave us the opportunity to better discriminate between our two Layout Methods.

The Projective Method produces sparse Topic Map layouts, in contrast with the Agglomerative Method which we designed to make packed layouts. Our participants were sensible to this, and showed a preference for layouts with a low density. In Chapter 5, we look at the visual features of Topic Map layouts and their impact of user confidence in more depth.

With the Layout Methods themselves, our participants reported to be more confident with the aggregation process presented by the Agglomerative Method. At the same time, some admitted to be confused with the Projective Method. This led them to designate the Agglomerative Method as a more suitable candidate to help them support and present decisions made from the Topic Map. Two issues seem to be weighting in that preference: the *process complexity* (e.g. Table 4.7a and 4.7c), and the *user familiarity* (e.g. Table 4.7b and 4.7e). We use these two issues as motivations to explore user confidence in Layout Methods in Chapter 6.

Chapter 5

Study 2 - Topic Map Layouts and User Confidence

Study 1 mainly aimed at exploring our participants' perception of mapping processes by means of Explanation Systems. We however found that they expressed variations of confidence with the Topic Map layouts. To further investigate this factor, we conducted a separate study, that we label *Study 2*.

The layout density seemed to particularly play an important role in the credibility and interpretability of a Topic Map. We use this insight in Section 5.1 to detail our research objectives. We then detail in Section 5.2 the modifications made to the agglomerative mapping process in order to produce the necessary stimuli to explore our research objectives.

We present the study design and procedure of Study 2 in Sections 5.3 and 5.4. Section 5.5 presents our results, and Section 5.6 discusses their relation to other research and their limitation. Finally we conclude Study 2 in Section 5.7.

5.1 Research Objectives

In Study 1, some participants targeted the Topic Map layout density as being a core factor for their credibility in the Topic Map. We argue that a Topic Map layout with a low density could allow for many characteristics: better cluster definition, reduced connectivity between items, distinctive shapes, positions, and other landmarks, etc. Each of these characteristics could lead to a decrease or increase in the user's cognitive load, and increase or decrease the credibility and interpretability of Topic Maps.

Given the variety of visual characteristics, we reckon there are multiple ways users exploit them to increase their confidence. We particularly consider two cases. Firstly, identifiable clusters enable users to chunk ideas and process the information displayed by a Topic Map faster. Secondly, as suggested by participants from Study 1, a lesser number of connections increases their quality, giving the user a guide for interpreting Topic Maps.

Our research objectives are therefore to find which of these visual characteristics are of importance for users, and assess how they affect their confidence in interpreting and explaining Topic Maps.

5.2 Modification of the Agglomerative Mapping Process

As we investigate the effects of layout density on user confidence and on the credibility and interpretability of Topic Maps, this study requires us to have a controllable mapping process. Our study design (Section 5.3) needs clusters to be shown to participants. As such, topics within clusters should not be visually separated when manipulating the Topic Map density.

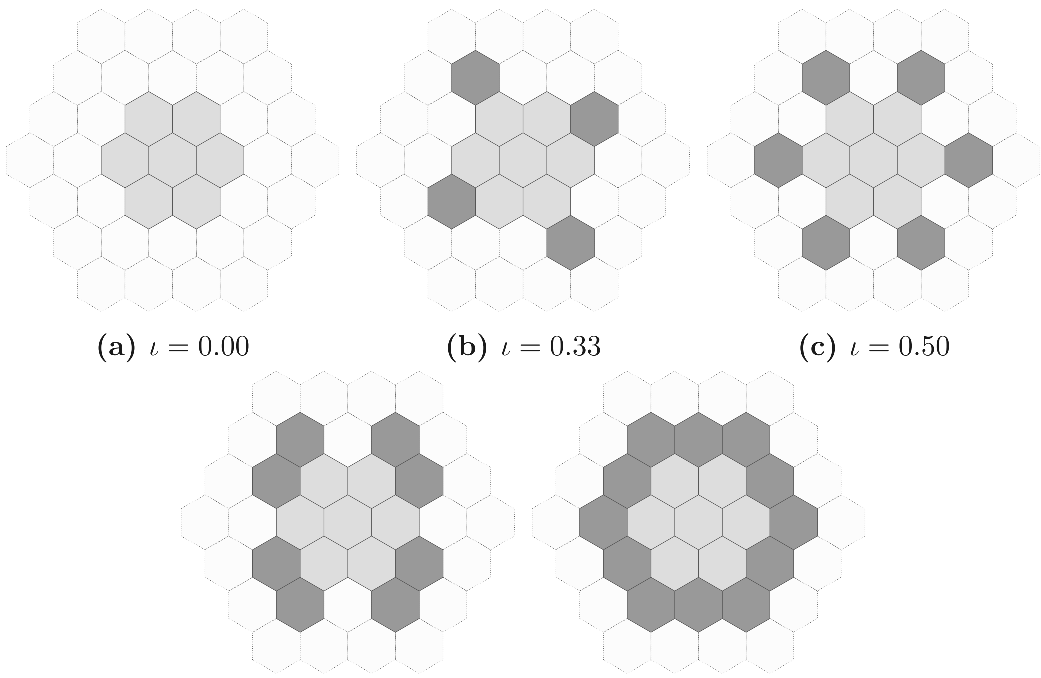
The projective mapping process can control the density of its Topic Map layout. However it is the product of two factors f_s and f_c, making its use more complicated, and the clustering process (k-means) presents no guarantee of compact clusters. We therefore decided upon modifying the agglomerative mapping process to introduce density control with one variable. The advantage of this Layout Method is that it positions topics based on their pre-established hierarchical clustering.

Our idea for generating sparser Topic Map layout is then to introduce space when merging two topic clusters during the relative positioning process. We control these spaces with an *isle factor*, ι, a percentage value describing how many of the cluster surrounding cells should be discarded during the merging process.

We modified the relative positioning process. When merging two hexagon clusters A and B:

- If A and B are part of the same topic cluster in the final Topic Map layout, continue the positioning process normally.
- Otherwise:
  - Get all the neighbour cells ${\eta^l}_A$ of A, with $l = 1$.
  - Given ι, choose ι percent of cells from ${\eta^l}_A$, in such manner that the chosen cells are evenly spread.
  - Temporarily merge the chosen cells with A, assigning a "blank" topic to them, and continue the positioning process normally.

Figure 5.1 illustrates this process with multiple values for ι.



(a) $\iota = 0.00$ **(b)** $\iota = 0.33$ **(c)** $\iota = 0.50$

(d) $\iota = 0.66$ **(e)** $\iota = 1.00$

Figure 5.1: Example use of the isle factor ι in the agglomerative mapping process. Given a topic cluster (in light grey), we choose ι percent of the surrounding cells (in dark grey) to be part of it for the positioning process. $\iota = 0.00$ (Figure 5.1a) corresponds to the initial agglomerative mapping process, and will produce dense Topic Maps, or "continents". $\iota = 1.00$ (Figure 5.1e) will produce spread Topic Maps, or "archipelagos". Values in between (Figures 5.1b to 5.1d) will produce various densities of Topic Maps, often representing "peninsulas".

5.3 Study Design

5.3.1 Stimuli

This study required us to create Topic Maps presenting a diversity of visual characteristics. We created these characteristics by means of density and cluster control.

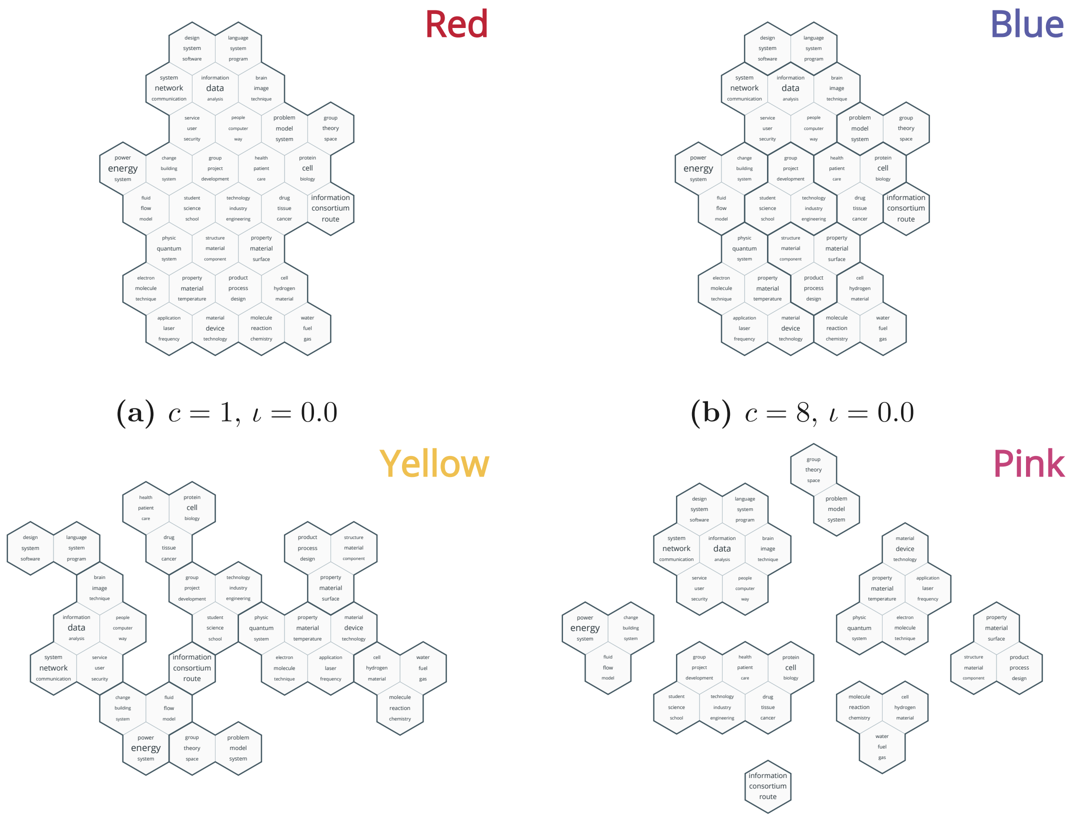
We generated these Topic Maps from only one topic model, to ensure that participants could not discriminate between the Topic Maps based on the topics. This topic model comprises 30 topics sampled from 10,000 documents selected randomly in our document pool.

Ten Topic Maps were generated, of which one control Topic Map presents the topics in one cluster, hence dense and fully connected (Figure 5.2a). The nine others each presents one of the products between three numbers of clusters ($c = 4$, $c = 8$, or $c = 10$) and three levels of density ($\iota = 0.0$, $\iota = 0.5$, or $\iota = 1.0$). Figures 5.2b and 5.2d and **??** show three examples of these Topic Maps, and Appendix E presents all of the ten Topic Maps used (page 131).

Each Topic Map was randomly assigned a colour as a title to aid identification during and across interviews [49]. We chose these colours from the list of recommended categorical colours [107]. Each Topic Map was rendered in high resolution (3000*2120 pixels), and adjusted to present a similar size of hexagonal units. We printed the Topic Maps on A4 sheets of paper, one Topic Map per sheet. It allowed us to present all the stimuli at once, not being limited by the size of a monitor.

5.3.2 Interviews

The research objectives we pose for this study require that we let our participants express their views freely. For this reason, we designed semi-structured interviews to gather our participants' thoughts. As with Study 1, we made use of a scenario to contextualise the task given to participants.



(a) $c = 1,\ \iota = 0.0$ **(b)** $c = 8,\ \iota = 0.0$

(c) $c = 10,\ \iota = 0.5$ **(d)** $c = 8,\ \iota = 1.0$

Figure 5.2: Three Topic Map stimulus examples. These stimuli are designed to display a range of density (controlled by ι) and number of cluster (controlled by c) in their layouts. Each Topic Map was randomly assigned a colour to aid identification during the interviews with the participants. Appendix E, page 131, presents the ten Topic Maps used.

The interview would start by presenting the participant with the Topic Maps laid out on a table in front of them. For each interview, the stimuli would be reordered randomly [49].

We would then give the participant their tasks for the study. These tasks would be for them to select or categorise the stimuli and discuss their choices and views on the stimuli, all with regards to a presentation scenario:

> "*You are going to explain the state of research of the Engineering and Physical Sciences Research Council (EPSRC) in front of your colleagues (other students, research associates, supervisors). Here are ten representations of this research. The words you see were extracted from grant data using a topic modelling application, which highlights words often used together in documents.*"

In addition to the Topic Maps, we also provided the participant with a set of coloured pens, and invited them to alter the paper stimuli, should they need to illustrate ideas.

The semi-structured discussion with the participant would then start. Our questionnaire was brainstormed within our research group and designed to probe the discussion towards the Topic Map layouts visual characteristics, and their use in the scenario. Figure 5.3 presents a rough organisation of the questions, although the participants were encouraged to speak their mind spontaneously and freely.

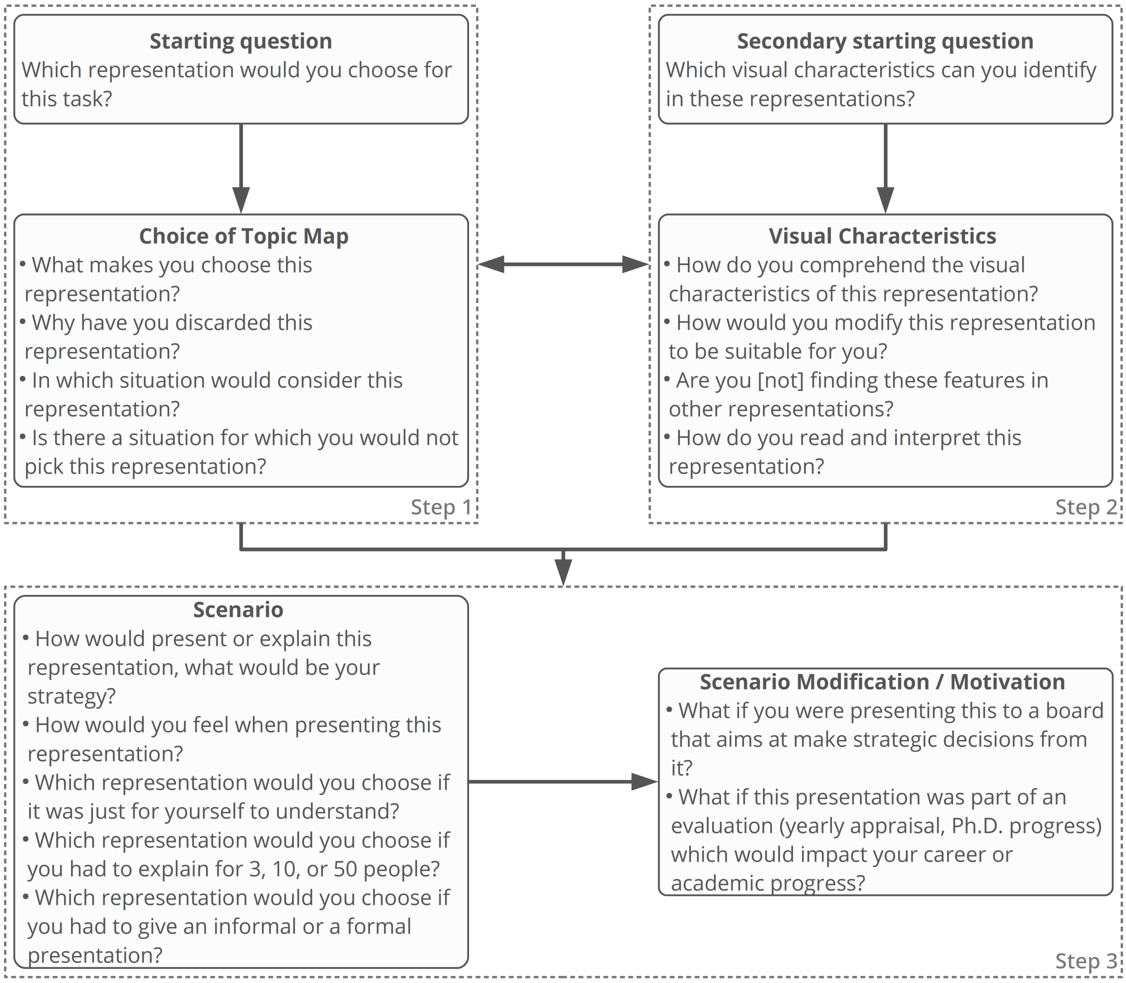


Figure 5.3: Interview flowchart. These questions were designed to probe the Topic Map layouts visual characteristics and their use in the scenario. We chose to have two start questions helping the participant getting into the discussion. The questionnaire also included scenario modification to bring vulnerabilities and motivations to the participants.

This organisation was designed to first let the participant choose one or more Topic Maps they would use (or not) in the scenario presented to them (step 1). Then, make the participants reflect on the visual characteristics presented in Topic Map layouts in details (step 2). And finally, have the participants talk through their use of the Topic Maps in the scenario, including variations bringing further vulnerabilities and motivations (step 3).

The organisation presented above was however different between participants. When a participant showed struggle with step 1, we directed the interview towards step 2. Likewise, we allowed the conversations to switch between step 1 and step 2 depending on the participant's priorities.

5.4 Procedure

We first piloted the study design, and did not encounter issues with the stimuli or interview design. Our pilot participant could easily identify with the scenario, and did not report difficulties in understanding our questionnaire.

We then conducted the study with 12 participants (P2.1 to P2.12). We recruited our participants using convenience sampling while targeting individuals likely to relate to the scenario (i.e. presenting results to an audience): Ph.D. students, undergraduates working as research interns, etc. We recorded the following demographic and experience information:

- age (optional);
- occupation (optional);
- frequency of use of static visualisations on a 5 points Likert scale;
- frequency of use of dynamic visualisations on a 5 points Likert scale;
- familiarity with creating data visualisations on a 5 points Likert scale;
- familiarity with data mining techniques on a 5 points Likert scale;
- familiarity with presenting to an audience on a 5 points Likert scale.

These background questions present an update from Study 1. First we have included presentation skills to fit with Study 2's scenario. Secondly we have decided to separate the user aspect (frequency of use of data visualisations) from the engineer aspect (familiarity with techniques). For the latter we also specify between data visualisation and data mining techniques. Since we increased the number of questions, we decided upon reducing from 7 points to 5 points Likert scale, and limit frustration from the participants [8].

We present our participants' background data in Appendix F, page 135. The participants' demographics show an age range from 20 to 46 ($M = 27.9$, $SD = 7.0$), and a cohort of 3 undergraduate, 1 postgraduate, and 6 research students, and 1 researcher. One participant preferred not to answer these questions. The background experience data confirm a participant pool of knowledgeable users for the interpretation and abstraction of visualisations, as well as experienced in presenting to an audience. Meanwhile, the lower familiarities with data mining and visualisation processes indicate a lower level of technical skills. This fits our targeted user profile.

As with Study 1, we had ethical approval to carry out this study, and gathered the participants' consent (Appendix B, page 126). The recorded data was anonymised and unlinked. For their time, our participants were rewarded with £10 Amazon vouchers.

All the interviews were carried in the same controlled environment. The participants were positioned in front of a desk on which the ten Topic Maps were presented in a 4×3 grid (the last row only presented two centred Topic Maps). For each interview, we randomised the order in which the Topic Maps were presented [49]. The interview length varied from 25 to 30 minutes. We recorded the interviews both on video and audio files, the video enabling us to capture the participants' interaction with the Topic Maps. These records were then transcribed, and analysed by one coder.

The codebook development followed an inductive approach. The coder first created an initial codebook based on two randomly selected transcripts. Then, an open coding process was kept, and consistency was ensured by making notes and recoding transcripts upon updating the codebook. The final codebook comprises of three categories of codes: *visual characteristics*, *user perception*, and *stimuli mentions*. Sentiment codings were first considered, e.g. for positive or negative statements. We however found during the first coding iterations that those were too confused, and isolating them resulted in a timely task with no benefit for the later data analysis.

The *visual characteristics* category contains codes regarding the graphical properties of the Topic Map stimuli:

- *Cluster*: clustering or grouping of items;
- *Connection*: connection between items;
- *Flow*: story, narrative, patterns, or flow of a Topic Map layout;
- *Landmark*: landmarks in the Topic Map layout;
- *Position*: position of items or groups of items in the Topic Map layout;
- *Shape*: shape or aspect of items or groups of items;
- *Size*: size of groups of items.

The *user perception* category contains code regarding the participants' opinions on the Topic Map stimuli:

- *Analogy*: analogy between Topic Maps and other concepts;
- *Change*: changes made to the Topic Map layouts;
- *Confidence*: expression of preference, choice, or confidence regarding Topic Maps and/or visual characteristics in the Topic Map layouts;
- *Information*: perceived information from the participants;
- *Memory*: memorisation (short or long term) of items in the Topic Map layouts.

Finally, the *stimuli mentions* category contains codes for each of the stimuli, allowing to count how many times participants mention them during the interviews. Additionally, the code *All* captures comments referring to all stimuli without distinction.

In the next section, we use this codebook structure to better understand and organise our participants' answers.

5.5 Results

5.5.1 Mentions of Topic Map Stimuli

Table 5.1 presents the counts of Topic Map stimuli mentions across all interviews. As the interviews where driven by the participants, these counts allow us to discern which of the ten Topic Map stimuli generated the most interest.

	Red	**Cyan**	**Brown**	**Blue**	**Green**	**Silver**	**Yellow**	**Purple**	**Pink**	**Orange**	**All**
c	1	4	8	10	4	8	10	4	8	10	
ι	0.0	0.0	0.0	0.0	0.5	0.5	0.5	1.0	1.0	1.0	
P2.1	3	0	2	1	4	5	22	0	8	1	3
P2.2	1	1	7	1	0	1	9	1	8	2	6
P2.3	7	2	4	4	4	8	21	1	15	12	1
P2.4	4	2	2	2	1	2	21	6	13	27	0
P2.5	1	6	7	8	8	1	3	3	20	27	0
P2.6	8	4	2	6	1	9	8	4	29	3	2
P2.7	0	1	2	4	4	10	5	2	11	9	0
P2.8	12	10	13	17	8	9	16	10	23	15	3
P2.9	6	2	6	0	1	24	18	0	27	11	2
P2.10	6	2	21	2	4	7	9	5	26	21	2
P2.11	13	5	5	5	5	12	28	1	12	21	0
P2.12	5	1	5	3	7	7	5	2	8	21	0
Total	66	36	76	53	47	95	**165**	35	**200**	**170**	19

Table 5.1: Topic Map stimuli mentions from participants, each stimuli represented by its colour label. These counts suggest that Topic Maps displaying a higher number of clusters and a lower level of density generated more comments and attention from the participants.

The patterns we observe in these counts reveal that Topic Maps combining a low level of density (controlled by ι) and high number of clusters (c) generated more discussion. To verify the significance of the effects of these variables on the participants' interests, we used a two-way repeated measures analysis of variance

(ANOVA) on these counts. We excluded our control Topic Map (*Red*, $c = 1$, $\iota = 0.0$) and the count for *All* stimuli from this analysis. Appendix G, page 137, details the results of these analysis.

Maulchy's test reveals that the assumption of sphericity of our data has not been violated for neither the number of clusters ($\chi^2(2) = 4.34$, $p = 0.11$), nor the density ($\chi^2(2) = 3.02$, $p = 0.22$), nor the interaction between these two variables ($\chi^2(9) = 9.61$, $p = 0.39$). We therefore assumed sphericity and did not correct the degrees of freedom.

The ANOVA presents the following results:

- The main effect of the number of clusters (Clusters) on the number of mentions by participants was significant ($F(2, 22) = 16.99$, $p < 0.05$). Post hoc test, using Bonferroni correction [34], shows that the differences between 4 clusters and 8 or 10 clusters were significant (both ps< 0.05), while the difference between 8 and 10 clusters was not ($p = 1.0$).
- The main effect of the level of density (Density) on the number of mentions by participants was significant ($F(2, 22) = 10.67$, $p < 0.05$). Post hoc test, using Bonferroni correction [34], shows that the difference between $\iota = 0.0$ and $\iota = 1.0$ was significant ($p < 0.05$), while the differences between $\iota = 0.5$ and $\iota = 0.0$ or $\iota = 1.0$ clusters were not (respectively $p = 0.066$ and $p = 0.425$).
- The number of clusters and level of density interaction (Clusters * Density) was significant ($F(4, 44) = 6.10$, $p < 0.05$).

In summary (see Table 5.2), this analysis allows us to conclude that Topic Map layouts displaying a larger number of clusters (8 or 10) stimulated significantly more comments and attention from our participants. Similarly, Topic Map layouts displaying completely separated clusters ($\iota = 1.0$) stimulated significantly more comments and attention from our participants compared to Topic Map layouts displaying completely attached clusters($\iota = 0.0$). Finally, our participants made significantly more comments on Topic Map layouts displaying both a large number of clusters, and a low level of density. This latter result was however expected by design, given that the Isle factor ι only reduces the density between clusters.

	Clusters	**Density**	**Clusters × Density**
Significance	Yes	Yes	Yes
	$c = 4$ vs. $c = 8$	$\iota = 0.0$ vs. $\iota = 1.0$	
	$c = 4$ vs. $c = 10$		

Table 5.2: Summary of the two-way repeated measure ANOVA results on stimuli mentions by participants.

These figures only indicate interest from our participants. Using the visual characteristics codes from our codebook, we explore the reasons for these interests in more detail in the next section.

5.5.2 Effects of Topic Map Layout Characteristics

Clusters

The presence of clusters in a Topic Map layout was often the first characteristic explicitly mentioned by our participants (ten out of twelve). As expected, the participants reported that it enables to structure the topics. This claim was often the result of a contrast between our control stimulus (the red Topic Map, see page 131) and the other Topic Maps (Table 5.3a to 5.3d).

The structure proposed by clusters helped our participants in organising the topics, increasing their confidence in the interpretation of Topic Maps. The red Topic Map stimulus was again used for contrast, as shown in Table 5.4a to 5.4c, but participants also spoke of other Topic Map stimuli (Table 5.4d and 5.4e).

In that context, six of the twelve participants commented on the size of clusters, and its impact on their confidence. For example, Table 5.5a to 5.5c describe how small identifiable clusters enables them to easily read, summarise, and understand the concepts presented by a Topic Map.

(a)	"I would say some of [the Topic Maps] indicate how this different grouping of topics comes together. [...] [The red Topic Map] just shows an overall map, I am not sure how related the different topic groups are. [...] In some cases, I see the darker lines might indicate [...] [the topics] sit in groups and they are attached to other related topics. So yes, smaller topics, larger areas, and obviously they are connected somehow together." (P2.1)
(b)	"In [the red Topic Map] you just have like a boundary all around and then in the middle, everything is connected, so you cannot really identify separate topics." (P2.3)
(c)	"[The red Topic Map] is really bad [...] because everything is one big block. [...] [The brown Topic Map] is very similar to [the red Topic Map], it is the same picture, but just with extra edges, so then at least this cuts me these words into nicer smaller parts." (P2.10)
(d)	"You have certain clusters which allow you to order the information [in the brown Topic Map], [in the red Topic Map] you do not understand what the main point is." (P2.12)

Table 5.3: Participants' quotes about clusters in Topic Map layouts. Having clusters enabled the participants to organise topics.

The distinction between the red Topic Map stimulus and the other stimuli, and the importance of "bite size" clusters, carried over to the participants' confidence in presenting to an audience. For P2.3 and P2.11, presenting a Topic Map displaying clusters has the advantage of enabling them to control the amount of information seen by the audience, and the course of their presentation (Table 5.6a and 5.6b). P2.2 and P2.7 then commented on how smaller sized clusters give them the confidence to explain a Topic Map layout better (Table 5.6c and 5.6d) .

The presence of clusters impacted our participants' confidence. In particular, medium and small sized clusters, which were presented by Topic Map stimuli with $c = 8$ and $c = 10$ (see Appendix E, pages 132 to 134), give a structure to Topic Map layouts, enabling our participant to confidently interpret these visualisations. This confidence extended to our participant explanation task, where clusters gave them control.

(a)	"[The red Topic Map], [...] everything is essentially grouped together, they are no distinctions between the smaller topics and the wider research areas. I would say that is the Topic Map that I think shows the least information." (P2.1)
(b)	"[With the red Topic Map] there is no real connection between anything, you can just start anywhere, or go anywhere from where you start. [...] I think that it is the opposite with [the yellow Topic Map], it helps me organize my thoughts." (P2.3)
(c)	"[The red Topic Map] [...] does not give as much information, [...] it is suggesting everything." (P2.11)
(d)	"If you see each of the [clusters], they have like a main title, and there also are subtitles, and I think they are connected together. So it is easy to remember everything, and easy to understand it." (P2.6)
(e)	"I prefer [the orange Topic Map]. [...] Because this way I already have some different clusters. [...] It is easier also for me to remember the position within this piece of paper. And it can be helpful for me to organise information, on the base of their position." (P2.12)

Table 5.4: Participants' quotes about the interpretation of Topic Maps using clusters. The structure offered by clusters helped our participants in reading and understanding the Topic Maps.

(a)	"It is more readable, like if I look at one cluster, in [the orange Topic Map], the clusters are small, so it is easier to grasp the overall idea of what they represent." (P2.5)
(b)	"You [...] need a sort of compromise of break, things broken up in little chunks, but not too much. So chunks in an even amount." (P2.8)
(c)	"I would then think more smaller units are easier to grasp than few large units." (P2.10)

Table 5.5: Participants' quotes about the size of clusters in Topic Map layouts. Small identifiable clusters led to a better interpretation of the data presented by Topic Maps.

Connections

Despite the importance of clusters, the participants commented more on the connections displayed in Topic Map layouts. By varying the level of density in the stimuli (controlled by ι), our participants experienced different level of connections between clusters, i.e. fully connected (e.g. Figure E.1d, page 132), partially connected (e.g.

(a)	"[The red Topic Map is] random in the sense that if you have to present, you can start anywhere and go anywhere." (P2.3)
(b)	"I would prefer to help [the audience] see the main things and get the most out of it as they can, instead of getting a bit lost in something like [the red Topic Map], where there is all of the information there, but it is not giving them any guidance." (P2.11)
(c)	"If I am trying to present it to somebody, I do not want to just overload them with what looks like too much, I want to [. . .] ideally have bite size chunks." (P2.2)
(d)	"The pink and the orange [Topic Maps] have smaller chunks, so I am probably partial to presenting those two, because I prefer dealing with bite size things. Cut things into bite size chunks, so that I can explain things." (P2.7)

Table 5.6: Participants' quotes about the use of clusters when presenting Topic Maps. With clusters, the participants felt like they could better control and pace their presentation.

(a)	"[The brown Topic Map] has more clusters, but it is so cluttered, you do not really pay attention to the stronger, thicker lines, when it comes to the clustering. [. . .] Having everything in one [clutter] is just a mess." (P2.5)
(b)	"I would probably say that these [red, silver, blue, brown, green, and cyan Topic Maps] even though they have got the sort of boundaries, [. . .] they are still not separated, and it does not feel has if they are being abstracted, they are still bundled up together." (P2.8)
(c)	"Because it is all together [in the brown Topic Map], it is harder to get the topic you are interested in." (P2.9)

Table 5.7: Participants' quotes about the perception of clusters in fully connected Topic Map layouts. Having a dense Topic Map perceptually removed the structure that clusters presented.

Figure E.1g, page 133), and not connected (e.g. Figure E.1i, page 134).

Eleven of our twelve participants communicated difficulties in using fully connected Topic Map layouts for the task given to them. The participants reported that it perceptually removes the structures conferred by clusters, for example Table 5.7a to 5.7c. But the main concern was the amount of connections displayed between clusters. Our participants felt this would impact both their interpretation confidence (Table 5.8a to 5.8c), and presentation confidence (Table 5.8d and 5.8e).

(a)	"There is too much connections [in the brown Topic Map] and it makes it a bit more difficult to understand, or to remember, memorize the different interconnections." (P2.1)
(b)	"[In the blue Topic Map] I see there are like thick lines and thin lines, so it is kind of also clustered, but they are all together. It is really hard to understand." (P2.2)
(c)	"[With the blue Topic Map] [...] I do not know where to start, whether it is in the middle, or the bottom and work up, or top and work down." (P2.8)
(d)	"[The blue Topic Map], I think it is difficult to understand, because it is all together, and [...] everything is connected, it is like one block. For me it is difficult to understand, and maybe to memorize and present that." (P2.6)
(e)	"Something like [the blue Topic Map] has so much connectivity [...] I would not really want to present it too much, it would take too long to sort of guide, even sort of allow people to kind of find the connections." (P2.11)

Table 5.8: Participants' quotes about the interpretability of fully connected Topic Map layouts. The abundance of connections between clusters made the Topic Map confusing for the participants, decreasing their interpretation and presentation confidence.

The partially connected Topic Map layouts received better comments. Seven participants expressed a positive confidence in using this type of Topic Map layout. It provided them with a path or narrative to follow, giving fluidity to their interpretation and presentation (Table 5.9a to 5.9e). Additionally, the participants reported that a moderate amount of connections between clusters in a Topic Map layout made the information more meaningful (Table 5.10a to 5.10c).

Despite these qualities, some participants were reluctant to use partially connected Topic Map layouts. For example, P2.2 and P2.6 thought the narratives presented by the layouts were forcing their interpretation, resulting in a lower confidence to use these Topic Maps (Table 5.11a and 5.11b).

Out of our twelve participants, nine were more confident in using Topic Map layouts displaying disconnected clusters. As expressed by P2.8 and P2.11, these Topic Map layouts are more interpretable for them and their potential audience (Table 5.12a and 5.12b).

(a)	"The reason why I picked [the yellow Topic Map] is because, if you want to go from one side to the other, the route is much more specific and you can just follow that." (P2.3)
(b)	"[The silver Topic Map] has got a nice follow through pattern." (P2.7)
(c)	"The worst case scenario is I would not know how to continue [the presentation]. [...] [The yellow or silver Topic Maps] would help me overcome that." (P2.9)
(d)	"One nice thing about [the yellow Topic Map] is that you can kind of have like starting at one point, following [down] and maybe branching off a bit." (P2.10)
(e)	"[The yellow Topic Map] is kind of guiding me through, it has got the same information [than other Topic Maps], but it is guiding me how to think about it." (P2.11)

Table 5.9: Participants' quotes about the narrative presented by partially connected Topic Map layouts. Having few connections between clusters gave the participants a narrative to follow when interpreting and presenting Topic Maps.

(a)	"I think what I like about [the yellow Topic Map] is that some of the areas are disjointed, however they are also connected, so I assume if there is a connection between these areas it is a strong connection, whereas if they are disjointed it is a much weaker connection." (P2.1)
(b)	"I would say that the information in [the silver Topic Map] seems to be more coupled together." (P2.9)
(c)	"I prefer something like [the yellow Topic Map], [...] it is easier to see where things are linked, and where things are not linked." (P2.11)

Table 5.10: Participants' quotes about the perceived information in partially connected Topic Map layouts. The participants perceived a better quality of information when only few connections are made between clusters.

(a)	"[The yellow Topic Map is] flowing somewhat to go in some sort of path, but because it goes in so many tangents, I am not sure about it, because there is not one long continuous thing, it goes on into side branches and that is where I am not sure how easily it would be to explain it." (P2.2)
(b)	"[The yellow Topic Map] is not helping me. Because it already has like the connections, and I prefer to make my own connections, on my own logic." (P2.6)

Table 5.11: Participants' quotes about the restrictive nature of connections in partially connected Topic Map layouts.

(a)	"I would say the pink or orange [Topic Maps] are probably the most readable out of all." (P2.8)
(b)	"I think [the orange Topic Map] is the most simplistic as well, simplistic for the audience to read [...] in a way that is the easiest one to present." (P2.11)

Table 5.12: Participants' quotes about the readability of disconnected Topic Map layouts.

(a)	"If my point is just to have broad idea of what is happening, I think that seeing how [clusters] are connected is already a step further in, for a higher level, clear separate areas are better." (P2.3)
(b)	"You cannot solve a problem as a whole, you have got to break it down. So that is why I think [the orange and pink Topic Maps] are much more understandable, and I think everyone else personally would." (P2.8)
(c)	"So if you are interested in showing something, in presenting some kind of topic, you would probably want to organise things, and [the pink Topic Map] is probably a better way." (P2.9)
(d)	"If I was organising information, I would choose something like [the pink or orange Topic Maps], because I could see the topics more easily, because they are easier to see." (P2.9)

Table 5.13: Participants' quotes about the identification of clusters in disconnected Topic Map layouts. Separated clusters aided the participants in perceiving those in the Topic Map layouts

The reason given by the participants is that these Topic Map layouts help the identification of clusters (Table 5.13a to 5.13d), unlike fully connected Topic Map layouts (Table 5.7).

Contrary to partially connected Topic Map layouts (Table 5.9), disconnected Topic Map layouts do not provide the participants with a narrative to guide their interpretation and/or presentation. Participants however did not view this as a negative point, and reported a strong confidence, stating their ability to build their own narrative (Table 5.14a to 5.14d).

The density level of Topic Map layouts had a large influence on our participants' confidence in interpreting and explaining Topic Maps. Fully connected layouts ($\iota = 0.0$, see page 132) perceptually removed the structure presented by clusters and

(a)	"I could probably do the same with [the pink Topic Map], with the chunks which sort of flow." (P2.2)
(b)	"For me it is sort of easier to have something like [the orange Topic Map]. Because then I can make my own kind of connections on it." (P2.5)
(c)	"I think [the pink Topic Map] would also make me more confident. Because here it is also harder to get lost. And even if I get lost, I could kind of just get to the next block or something. So I would not lose so much of my story." (P2.10)
(d)	"[In the orange Topic Map] I create the order, but I know where the information is." (P2.12)

Table 5.14: Participants' quotes about the narrative of disconnected Topic Map layouts. The absence of connections between clusters gave participants the freedom to create their own narrative, improving their confidence.

in return confused the participants with the many narratives it presented. With partially connected Topic Map layouts ($\iota = 0.5$, see page 133), our participants gained confidence, as these provided them with a narrative to follow. Disconnected layouts ($\iota = 1.0$, , see page 134) received an even better response. The participants reported a better cluster identification, which increased the Topic Map interpretability and explainability. They also expressed their confidence in being able to construct their own narrative for the Topic Map.

Landmarks

The third visual characteristic impacting our participants' confidence are landmarks. The interviews revealed two kinds of landmarks relevant to our participants: the size of labels in topic cells, and the shape of regions in the Topic Maps. The latter includes clusters or particular arrangements of clusters. Example of such landmarks are shown in Figure 5.4.

The participants commented on the size of texts in maps. As shown by Table 5.15a to 5.15c, the participants used this variation of font size as anchor points for their narrative. They generally reported an increase of interpretability. Additionally, P2.11 expressed that this type of landmark helps explainability (Table 5.15d).

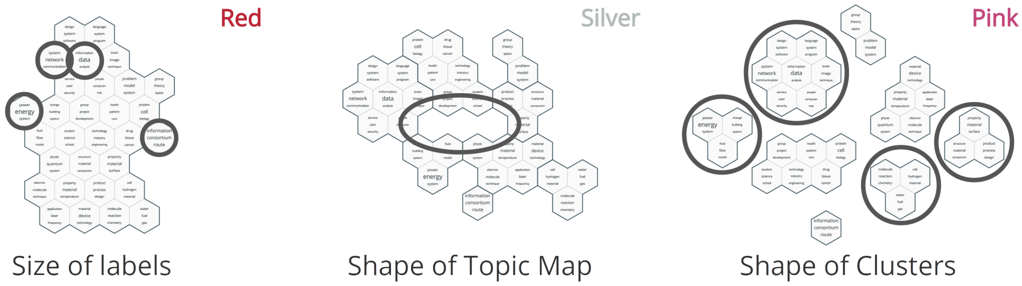


Figure 5.4: Examples of visual landmarks as identified by our participants. These landmarks include size of labels, and striking shapes in the Topic Maps.

(a)	"I would probably look at the bold [large text] first and then the alternate text, you know the font, style or sizing. [...] I am not going to start just because it is at the top, I would start probably because it is the largest [text]." (P2.2)
(b)	"Each of the [clusters], they have like a main title, and there also are subtitles [...]. So it is easy to remember everything, and easy to understand it." (P2.6)
(c)	"For me a larger text font or bolder represent a start of something, whether it is the start of an entire representation, or the start of a new area of the presentation, that is what that means to me." (P2.7)
(d)	"I think it is quite important to guide the audience, because [...] they can get distracted by a lot of different things." (P2.11)

Table 5.15: Participants' quotes about the textual landmarks in Topic Map layouts. The few topics with larger font allowed the participants to have anchor points to read and present the Topic Maps.

Another type of landmark used by participants are the shape of clusters in Topic Map layouts. P2.2 for example, commented that the shapes of certain clusters facilitate interpretability (5.16a). P2.3 saw shapes as a mean to identify and memorise information for their presentation task (5.16b).

The green and silver Topic Map stimuli both displayed holes or gaps in their layouts. This characteristic divided the participants. P2.7 and P2.8 for example, along with three others, saw it as a way to pace their interpretation, and organise their presentation (Table 5.16c and 5.16d). P2.5, P2.12, and two other participants however were not confident with this characteristic (Table 5.16e and 5.16f), stating that they would simply not be capable of accounting for it (Table 5.16g).

The participants used landmarks in the Topic Map layouts to build up their

(a)	"Everything in [the cluster] is relatable to that central piece of information. At least for the round [cluster in the pink Topic Map]." (P2.2)
(b)	"Some of [the clusters with three topics] are facing up, some of them are facing down, [...] even if they have the same size the disposition also helps, for example [in the orange Topic Map] we have this group of five [topics] and this group of five [topics], with different orientations, that would also be helpful." (P2.3)
(c)	"It makes me feel like I want to go around it. Like there is some structure for me to go around it. So I would follow around." (P2.7)
(d)	"I think [having a gap] is good, [...] it feels as if it gives more time to process information, if that makes sense." (P2.8)
(e)	"I feel like something is missing [in the green Topic Map], because this is like a whole thing and it is just empty pieces. [...]. I have no idea why you do this [gap], it is weird." (P2.5)
(f)	"[Having a gap] is something that does not make any sense, I would try and forget about it." (P2.12)
(g)	"While presenting it, I would always be looking at the empty spot [...] I feel like something is missing, and if someone asks me, I can not tell why it is empty. Because it does feel like it is a separation, it just feels like it is empty." (P2.5)

Table 5.16: Participants' quotes about the shapes displayed in Topic Map layouts. The shape of clusters helped the interpretability and memorisation of Topic Maps. When confronted with Topic Map layouts presenting a hole, participants either used it to help their interpretation, or saw in it a mistake that would distract their audience, decreasing their confidence.

confidence in interpreting and explaining Topic Maps. These landmarks included the size of labels and the shape of regions in the Topic Maps. They notably provided cues for the participants' interpretation, memorisation, and explanation of Topic Maps.

5.6 Discussion

Three main visual characteristics were highlighted by our participants during this study: clusters, density, and landmarks. Their significance were however already known prior to our work [9, 83, 88, 100, 109]. This study reinforce this importance and set it within the context of user confidence.

We believe these results showed the benefits, for mapping processes, to incorporate varying levels of distances. While irregular layouts generally implement those, we demonstrate here their use and advantages on regular layouts too.

There are however limitations in the implementation we present in Section 5.2. The spaces we introduce could be seen as distorting the Topic Map, with regard to the similarity data. We although argue that these spaces are derived from the data as well, given their use based on the clustering information.

Nevertheless, we acknowledge the possibility for future work to implement an optimisation of the relative positioning algorithm, were more spaces could be introduced when the similarity between clusters decreases.

As with Study 1, we also acknowledge a limitation in the hypothetical nature of our participants statements. The same pragmatic constraints impeded the possibility of an experiment where participants would choose a Topic Map, motivate their choice, present it to an audience, and report on their degrees of confidence throughout this process.

5.7 Conclusion

The research objectives of this study were to identify which visual characteristics are important to users, and assess the effects of these characteristics on the users' confidence in their interpretation and explanation tasks.

To create a rich set of visual characteristics, we first modified the agglomerative mapping process. By incorporating an *isle factor* in the merging process of the agglomerative mapping process, we introduce noise, and create sparser Topic Map layouts. We describe this process in Section 5.2.

We detail in Sections 5.3 and 5.4 our experimental design and procedure to explore the research objectives.

		Provides		Effect on
		Structure	**Narrative**	**User Confidence**
Clusters	$c = 1$			✘
	$c = 4$			✘
	$c = 8$	●		✔
	$c = 10$	●		✔
Density	$\iota = 0.0$			✘
	$\iota = 0.5$		●	✔
	$\iota = 1.0$	●	●	✔
Landmarks	Label size		●	✔
	Shape of clusters	●	●	✔
	Hole in Topic Map		●	✔/ ✘

Table 5.17: Findings summary for Study 2. In the *Provides* column we highlight which parameters provide structure and/or narrative to the interpretation of the Topic Map layout (●). In the *Effect on User Confidence* column, we indicate whether these parameters allowed the user to feel more confident (✔) or less confident (✘).

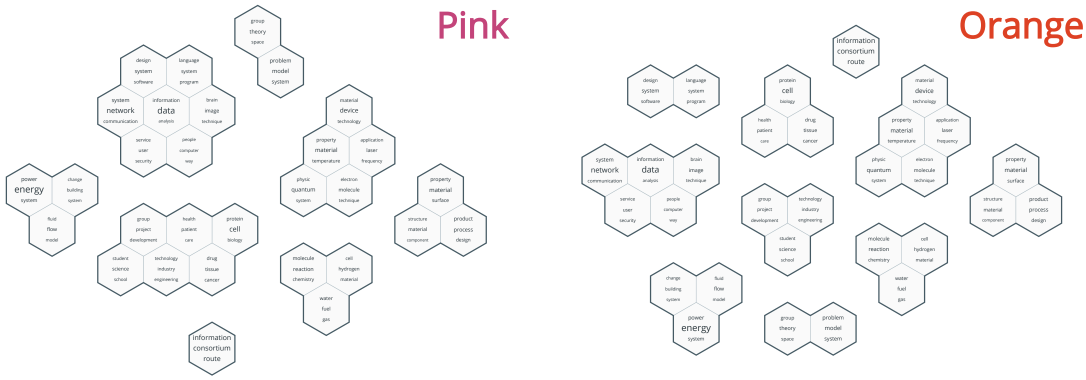
The results that we present in Section 5.5 highlight three visual characteristics of Topic Map layouts identified by our participants: clusters, connections, and landmarks. We summarise these results in Table 5.17, were the ticks are determined based on our participants' statements.

Having clusters allowed the participants to organise topics and improved their confidence in both interpreting and explaining Topic Maps. This improvement was noteworthy for Topic Map stimuli with eight or ten clusters.

The different level of density in our stimuli allowed the participants to comment on the connections in Topic Map layouts. Fully connected Topic Map layouts perceptually removed the organisation presented by clusters, and proposed too many links between clusters. Partially connected Topic Map layouts enabled the participants to create narratives for their interpretation and presentation tasks. With disconnected Topic Map layouts participants were able to better identify the cluster organisation, and construct their own narratives.

Finally, the landmarks in the Topic Map layouts helped the participants by presenting anchor points to structure their interpretation, and pace their explanation of Topic Maps.

These results lead us to recommend designers to generate Topic Maps with many disconnected and unevenly shaped clusters. As examples, the Topic Maps labelled as "Orange" and "Pink" in our study fit this description (Figure 5.5).



(a) $c = 8$, $\iota = 1.0$ **(b)** $c = 10$, $\iota = 1.0$

Figure 5.5: Examples of Topic Map layouts that have enabled improvement in the user's confidence in their ability to interpret and explain Topic Maps.

Study 2 explored Topic Map layouts as a continuation from the results of Study 1 (Chapter 4). In the next chapter (Chapter 6), we will present Study 3, which also follows up on the results of Study 1, focusing this time on Layout Methods and user confidence.

Chapter 6

Study 3 - Mapping Processes and User Confidence

In Study 1 (Chapter 4), our participants found the Agglomerative Method clearer and reported having a greater confidence explaining this method. The study scope however did not allow us to investigate this preference further. We therefore conducted a follow-up study to further explore Layout Method preferences. We label this work *Study 3*.

In particular, we found that the results of Study 1, for the preference of Layout Method, were the product of two aspects: the process complexity and the user familiarity. We use these findings as basis to describe six research objectives in Section 6.1. These objectives aim at contrasting the impacts of the two Layout Methods (agglomerative and projective) on user confidence. We then detail our study design in Section 6.2.

After detailing our procedure (Section 6.3), we present the results for each of the six research objectives in Section 6.4. Finally, we conclude Study 3 in Section 6.6.

6.1 Research Objectives

Examining the results from Study 1, we have isolated two themes affecting the user confidence in Layout Methods. The first is the *process complexity* (from a user point of view). The second is the *user familiarity*.

As presented by Hollnagel [54], system complexity can be defined as the product of: the number of items in the system, the number and interpretability of interactions between items in the system, and the predictability of change in the system.

We defined user familiarity as the combination of the user's background knowledge, and their canonical view of a mapping process, that is, their "instinctive" idea of how a mapping process operates, or how they would do it themselves. With further consideration, we extended our definition of user familiarity to incorporate the user's perception of fitness between the process, the Layout Method, and the result, the Topic Map.

Based on these themes and sub-themes, we compiled a set of twenty-two questions during a brainstorming session within our research group. As suggested by Adams and Cox [2], we grouped these questions in six categories to ease the participants workload during the interviews.

- **Identification** of the components and behaviours of a Layout Method:
  - How many units or components do you see in the application?
  - Which units or components can you identify in the application?
  - Which unit or component behaviours can you identify in the application?
  - What relations between units or components can you identify in the application?
  - How do you feel about those behaviours and relationships between units or components?
- **Confidence of memorisation** of a Layout Method:
  - * Could you describe the layout process without looking at the application?
  - How much do you feel you would need to remember to describe the layout process?
  - How would you memorise the layout process?
  - How much do you feel you would remember if I ask you about the layout process in a few days?
- **Confidence of presentation** of a Layout Method:

  - Does the application require modifications according to you?
  - Would you introduce notions before presenting the layout process?
  - * How would you present the layout process?
- **Perceived difficulty** of a Layout Method:
  - How would you qualify the length of the layout process?
  - How much attention does the mapping layout requires?
  - Would the difficulty level of the layout process fit a non-technical audience?
  - On a scale, how much do you feel you have to understood the layout process?
- **Canonical view** of a mapping process:
  - How would you describe the layout process logic?
  - How would you rate the difficulty of this approach?
  - Would you have laid out the concepts following another logic?
- **Result fitness** between a Layout Method and its resulting Topic Map:
  - Do you feel like the application explained everything about the resulting concept map?
  - Could you foresee the resulting concept map while interacting with the application?
  - How much of the layout process do you see in the resulting concept map?

Identification, memorisation, and presentation correspond to tasks the user has to perform when explaining a Topic Map and its Layout Method. We therefore believe it is necessary to investigate how their confidence can be affected during these tasks.

In our questionnaire, the questions marked with an * require the participant to perform the memorisation and presentation tasks. Testing their ability in these tasks is however not our objective. Instead we focus here on their perception of their confidence in doing so, hence the use of hypothetical questions.

We also believe that exploring the perceived difficulty, canonical view, and result fitness will allow us to obtain insights into the users' cognitive load when interpreting a mapping process, and how their confidence can be affected by it.

Contrasting participants' views of the Agglomerative Method and the Projective Method along these six categories constitutes our research objectives.

6.2 Study Design

6.2.1 Interviews

In this study, we make use of the questionnaire defined with our research objectives (Section 6.1). As with Study 1, we contextualise this discussion with a scenario.

The interview would start by introducing Topic Maps and topic modelling to the participant. They would then be instructed to consider the scenario and discuss the stimuli through a series of questions. The scenario presented to the participant is as follow:

> "*You are asked to present and explain this representation of a research portfolio in front of a non-technical audience. The quality of your explanation will impact your academic/career advancement. To aid your preparation for this task you are provided with an interactive presentation of the layout mapping process.*"

Following an introduction to the stimulus application, the participant would be asked to interact with it for five minutes, period after which the interview would start. In the interviews we use the twenty-two questions outlined with our research objectives (Section 6.1).

In contrast to Study 1, Study 3 aims to explore the difference in user confidences between the Projective Method and the Agglomerative Method in more depth. In that regard, we decided to focus the participants' attention, and restrict their session to the use of one Layout Method. We made this restriction in order to reduce participant fatigue, and allow for more discussion and insights. Finally, we aimed to avoid comparisons, a problem that we encountered in Study 1, where participants had difficulties in communicating further than simple comparative judgements.

6.2.2 Stimuli

The stimuli presented in Study 3 consists of Explanation Systems following the design we present in Section 4.1.

As detailed in the previous section, only one Explanation System was shown per participant. The Explanation System was accessible to participants for the entirety of the interview, allowing in-depth contextualised comments.

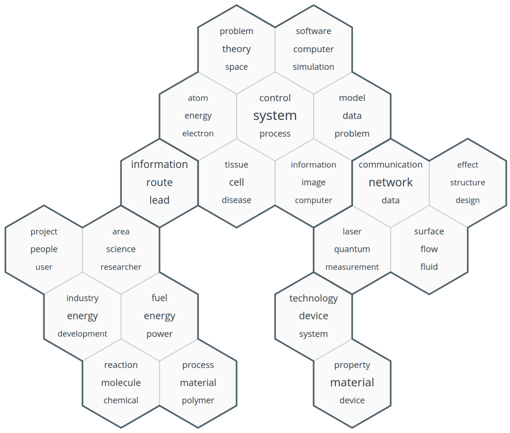
We created these stimuli using four topic models of 20 topics. These topic models were generated from $2,000$ randomly picked documents each. We applied mapping processes to obtain four Topic Maps (one per topic model), two using the Agglomerative Method and two with the Projective Method. To obtain similar Topic Map layouts, we manually tuned the topic models used by, and the parameter values for, the mapping processes. Figure 6.1 shows these Topic Maps and the parameters used for each of them. The Explanation Systems for each of the four Topic Maps were then generated, Figures 6.2a and 6.2b present two examples of these stimuli.

As in Study 1, the Explanation System views were presented in three parts:

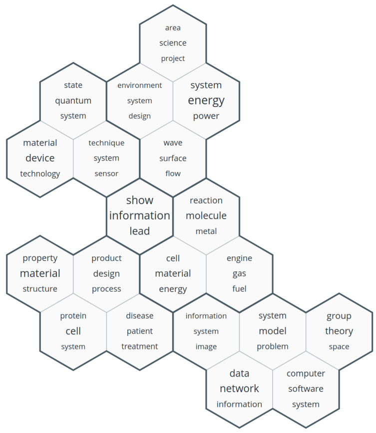
- the Explanation System on the left-hand side;
- a descriptive text of the Explanation System actions on the top right-hand side, along with buttons allowing the participant to step through the Explanation System;
- a minimap of the final Topic Map layout on the bottom right-hand side.

In Study 1, it was noted that participants did not fully use the descriptive text. In order to reduce the amount of animations presented to the participants, we decided upon changing the text to a fixed two sentence description of the Layout Method. We also added the topic labels in the minimap, since participants would not experiment with the Topic Map view.

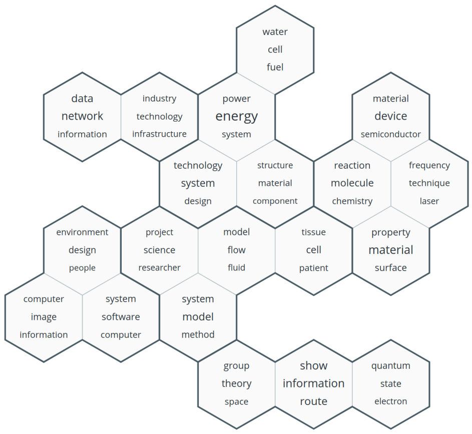
The interactions between the minimap and the Explanation System were kept. Hovering over a topic highlights it in both the Explanation System and the minimap (Figure 6.3a). Clicking on a topic marks it, with two marker colours available



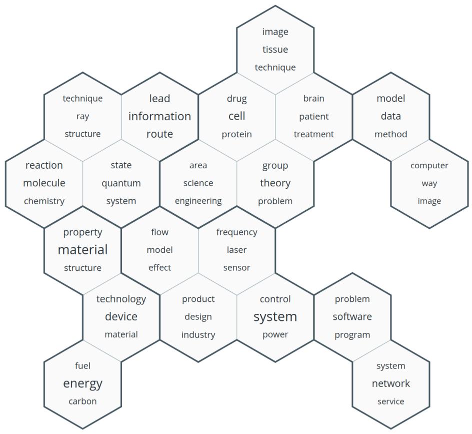
(a) Agglomerative, $c = 6$, $\iota = 0.6$



(b) Agglomerative, $c = 6$, $\iota = 0.7$



(c) Projective, $c = 6$, $f_s = 1.5$, $f_c = 4.0$



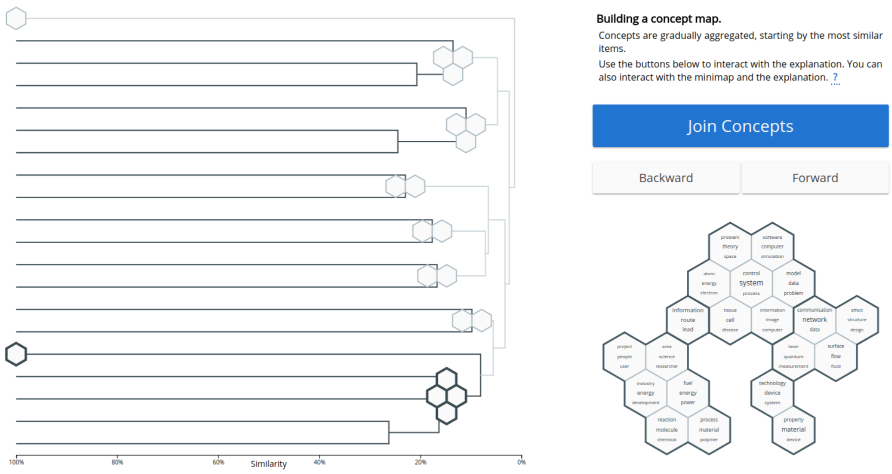
(d) Projective, $c = 6$, $f_s = 1.5$, $f_c = 5.0$

Figure 6.1: Topic Maps of the Explanation System stimuli used in the study.

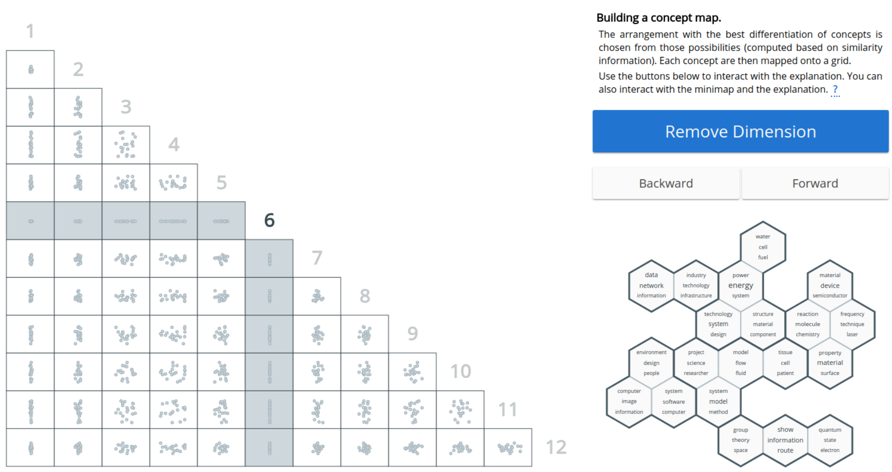
(Figure 6.3b).

6.3 Procedure

We conducted a pilot study, in which the participant reported issues with the instructions given to them. Mostly, they had trouble identifying the relations between elements of the interface. We corrected this issue by including a printed guide (which we would read to the participant), highlighting the main parts of the interface (explanation, controls, and minimap), their role and interactions. Furthermore, they often tended to reflect more on the data (i.e. the topic labels) rather than the Layout Method, despite the interviewer's reminder of the study's subject. We therefore added these instructions in the task sheet given to the participant, and frequently



(a)



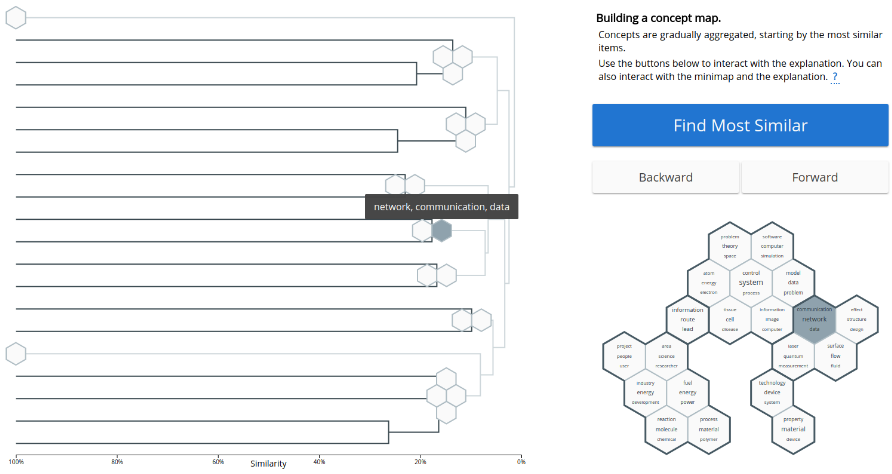
(b)

Figure 6.2: Example Explanation System stimuli used in this study. Figure 6.2a shows the agglomerative Explanation System stimulus corresponding to the Topic Map presented in Figure 6.1a. Figure 6.2b shows the projective Explanation System stimulus corresponding to the Topic Map presented in Figure 6.1c.

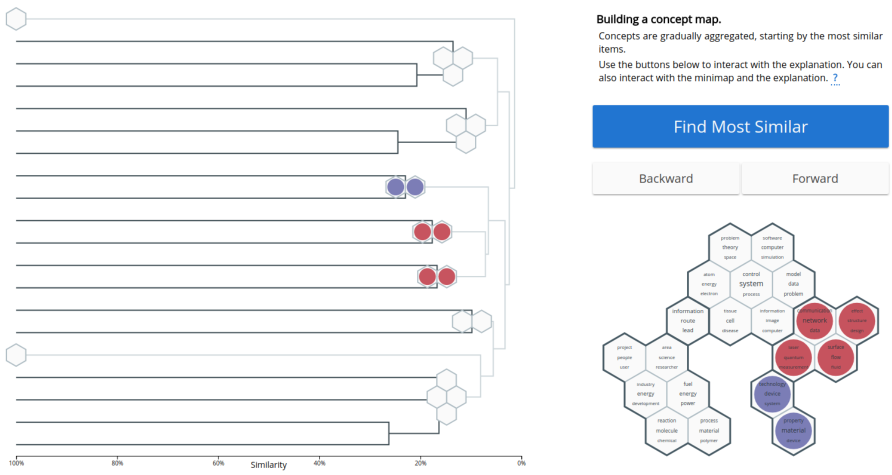
reminded them of it, when needed, during the interview.

We then conducted the study with 16 participants (P3.1 to P3.16), half experimenting with an agglomerative Explanation System, and the other half with a projective Explanation System. The participants were recruited using convenience sampling. We recorded the following demographic and experience information:

- age (optional);
- occupation (optional);
- frequency of use of static visualisations on a 5 points Likert scale;
- frequency of use of dynamic visualisations on a 5 points Likert scale;



(a) Example of highlighting interaction.



(b) Example of marking interaction.

Figure 6.3: Example of interactivity in the Explanation System stimuli. The combination of highlights and markers allows participants to find and track topics throughout the explanation. The example used here is with the agglomerative Explanation System, the same interactions were implemented with the projective Explanation System.

- familiarity with creating data visualisations on a 5 points Likert scale;
- familiarity with data mining techniques on a 5 points Likert scale;
- familiarity with presenting to an audience on a 5 points Likert scale.

In Section 5.4, we explain our motivation for updating the demographic and experience questionnaire we used in Study 1.

We present our participant's background data in Appendix H, page 140. The participants' demographics show an age range from 20 to 36 ($M = 25.7$, $SD = 4.9$), and a cohort of 6 undergraduate, 4 postgraduate, and 4 research students, 1 researcher, and 1 lecturer. This data suggests average competencies for visualisation interpretation, technical knowledge, and presentation familiarity. None of the participants reported being an expert. The Layout Method presented was randomly assigned to the participants [49].

As for the two previous studies, we had ethical approval to carry out this study, we collected the participants' consent (Appendix B, page 126), and we anonymised and unlinked the recorded data. The participants were compensated using £10 Amazon vouchers.

The interview length varied from 27 to 42 minutes, the latter being an exception, with an average of 30 minutes. The stimuli were presented in a controlled environment, and displayed on a 24 inch monitor with a 1920*1080 pixels resolution. The monitor was color-calibrated to ensure a consistent display of the views for all participants. Each interview was audio taped, before being transcribed.

The transcripts were coded by one coder. The codebook development did not require an open coding approach. Given the interviews' structure, we were able to code them following the research objectives we set for this study (Section 6.1):

- *Identification*;
- *Memory*;
- *Presentation*;
- *Perceived difficulty*;
- *Canonical view*;
- *Result fitness*.

In addition, the code *Clarification* was used to categorise the participants' requests for help on the interpretation of the Layout Method. Sentimental statement were not coded due to the difficulty to isolate those in the participants' answers.

6.4 Results

In this result section, we will contrast the comments from our two groups of participants. *Group 1* constitutes the pool of participants that experimented with the two agglomerative Explanation Systems, comprising of P3.1 to P3.8. While *Group 2* represents the pool of participants that experimented with the two projective Explanation Systems, comprising of P3.9 to P3.16.

After examining the Clarification code, we structure the analysis along the six research objectives we set for this study.

6.4.1 Clarification

In Group 1, only one participant, P3.4, requested clarifications of the Agglomerative Method. These requests concern the unicity of the dendrogram tree, and the similarity measure used.

In Group 2, six of the eight participants requested clarifications of the Projective Method. These clarifications concerned the multi-dimensional nature of the data presented in the projective Explanation System, in particular:

- The scatter-plot matrix represents a multi-dimensional data space.
- Every scatter-plot in the matrix contains one instance of all the topics.
- The scatter-plot matrix displays different arrangements of topics using the dimensions.

The clarifications were only given after the participants had answered questions from the Identification category.

6.4.2 Identification

Identifying components in the agglomerative Explanation Systems did not represent a challenge. All of the participants in Group 1 identified the nodes as topics in the Explanation Systems, and six out of eight described the dendrogram and its role in the Agglomerative Method (Table 6.1a to 6.1c). When discussing the number of elements, the participants reported that although it seemed considerable at first, the Agglomerative Method simplified it over the course of its process, as explained

(a)	"Twenty [...] nodes. [...] There are twenty lines, and then they form together, to create ten, [...] and then ten to five, and five to three, three to two, two to one. [...] Nodes and lines, branches." (P3.2)
(b)	"The nodes [...] you have got the links. [...] You have got the nodes joining together as well. [...] And you have got the similarity thing as well." (P3.3)
(c)	"So we have got the axis, we have got all of the links that show hierarchy, we have got like individual items when they start over here." (P3.8)
(d)	"Once you step through it, I would not say it is too many. [...] I was not sure what everything meant initially, but [...] once it starts stepping, I was like "okay, now I see what is happening". So yes, I would not say it is too many." (P3.5)
(e)	"At a first glance it looks too much, but when you play around the application, it is easy to understand." (P3.6)

Table 6.1: Participants' quotes about the components identified in the Agglomerative Method.

by P3.5 and P3.6 in Table 6.1d and 6.1e.

All the participants in Group 1 described joining or aggregation behaviours in the Agglomerative Method. Six of the eight participant in the group indicated that this process displayed simple component behaviours (Table 6.2a and 6.2b), that are easily explainable (Table 6.2c). P3.6 was the only one noting that it may require "a little background" (Table 6.2d).

The identification of components in the Projective Method was mixed in contrast. While P3.16 was able to confidently recognise elements in the Explanation System (Table 6.3a), the other seven participants of Group 2 showed more hesitation, despite being correct in their interpretation, for example in Table 6.3b to 6.3d. Comments concerning the number of elements were mixed too. While participants perceived the scatter plot matrix as displaying a large quantity of information, P3.9 also observed that it allows the repetition in the Explanation System, which enables a better interpretation (Table 6.3e and 6.3f).

The behaviours used in the Projective Method posed more issues. In seven cases out of eight, the participants were able to identify that the projective Explanation

(a)	"[Interviewer: Which component behaviours can you identify?] Join, join behaviour. Combination. [...] It is simple, nothing I have not seen before." (P3.2)
(b)	"As we move from the left to the right, aggregation happens, so we group things together and then each of the regions can be treated as new joined region. [...] I guess it is kind of synonymous to grouping. [...] I would say it is fairly clear." (P3.4)
(c)	"It slid over, and they joined. [...] I am always nervous when presenting, but I would feel fairly comfortable [...] I feel like I would know what to say." (P3.5)
(d)	"The nodes grouped up together [...] they grouped together at the end and made the final map. [...] For a non-technical person I feel like it would be challenging to explain it, but for someone who has a little background in this, [...] it would be easy for them to explain. [...] I would say I can explain it now." (P3.6)

Table 6.2: Participants' quotes about the behaviours identified in the Agglomerative Method.

(a)	"So there is a grid. There are rows, there are columns. And there are the [...] concepts. [...] [The number of elements] is just about right." (P3.16)
(b)	"You have the points, each of the concepts plotted. And you have different groups of them, like different ways, I guess." (P3.9)
(c)	"[There are] scatter plots inside of [the boxes], I guess. [...] [With] these different concepts. [...] That is just what it looks like to me." (P3.12)
(d)	"I assume, each one of those [hexagons in scatter plot] is one of them [topics in Topic Map]. [...] But I do not understand what each row or column represent. [...] I guess it is a relation through an algorithm that is trying to organise them. But I really do not know." (P3.14)
(e)	"It is a bit daunting I guess, I do not know, if you do not know the points. But [...] I do like the amount with the animation, because you show the process going from more than once, which kind of makes people get that, or understand it better." (P3.9)
(f)	"I identified squares yes. [...] [It is] not too much, it is moderate. [...] The [topics] inside [the scatter plots] [...] that is too much." (P3.10)

Table 6.3: Participants' quotes about the components identified in the Projective Method.

(a)	"I did not understand why they have different structures in each square. In some of them they are scattered, some of them are accumulated. Is there a reason behind that? [...] I did not know what was the criteria for eliminating the rows and the columns. [...] If I would know it, it would not sound confusing." (P3.10)
(b)	"Is there some kind of relationship between the items in the rows and in the column? [...] I do not know what that is. [...] [I am] slightly confused by it." (P3.14)
(c)	"If I am being honest, I do not know, [...] it is not completely intuitive. [...] It does not really [...] shout out to you its general purpose." (P3.15)
(d)	"Boxes went away, into more detail [...] I did not really understand, like what the sliding stuff was doing, but the parts after that [the grid assignment], it made sense." (P3.12)

Table 6.4: Participants' quotes about the behaviours identified in the Projective Method.

System displayed different arrangements of topics before removing all but one. However, the reasons behind this remained obscure, confusing, and non-intuitive to the participants (Table 6.4a to 6.4c). Only P3.12 commented on the second part of the Projective Method, saying that it "made sense", as opposed to the dimensionality reduction stage (Table 6.4d).

We observed a clear difference in our participants' answers when they were tasked to identify the components and behaviours of the Layout Methods. Participants in Group 1, experimenting with the agglomerative Explanation System were able to identify components and behaviours with confidence. Participants in Group 2, experimenting with the projective Explanation System, showed less confidence, despite being correct in their interpretation. This was particularly striking during the interpretation of the Projective Method's behaviours.

These results are in accordance with the requests for clarification that we detail in the previous section. The participants experimenting with the Projective Method were unable to confidently grasp the concepts concerning the multidimensional nature of its data. In comparison, showing only one instance of the topics in a list, and proposing a recursive process of aggregation, as shown by the Agglomerative

(a)	"So we are taking different concepts, rating their similarities, and then grouping the most similar concepts together." (P3.1)
(b)	"I mean I do not see why I could not [describe without looking at the screen]. [...] I feel I can, like I am 99 percent sure I could [remember after a few days], yes." (P3.7)
(c)	"So the most similar concepts are grouped together, recursively, to create ever larger regions. [...] I think I would [remember after a few days], I think it is fairly straightforward. Maybe not the implementation, but how it visually looks." (P3.4)
(d)	"It is not overly complex. Yes, I would say it is fairly rememberable. [...] I would remember the hexagons sliding across and grouping. [...] I would remember visually." (P3.5)

Table 6.5: Participants' quotes about their ability to memorise the Agglomerative Method.

Method, allowed the participants of Group 1 to feel more confident about their interpretations.

6.4.3 Confidence of Memorisation

All of the participants of Group 1 were able to recall the Agglomerative Method when asked to describe it without looking at the stimulus application, for example P3.1 in Table 6.5a. This ability could carry over long term tasks, as stated by P3.7 in Table 6.5b. The participants attributed this to the visual aspect of the Explanation System and the simplicity of the Agglomerative Method (Table 6.5c and 6.5d).

After querying their ability to memorise the Agglomerative Method, the participants of Group 1 were asked to detail their memorisation strategy. For them the simplicity of the Agglomerative Method would suffice to memorise it, for example with P3.1 and P3.6 in Table 6.6a and 6.6b. P3.2 and P3.7 further explained that the familiarity with the concept of a hierarchical tree is the cause for this simplicity (Table 6.6c and 6.6d). In addition to the simplicity of the process, some participants remarked that the visual aspect of the Explanation System would give them cues to remember the Agglomerative Method (Table 6.6e and 6.6f).

(a)	"It is pretty reasonably straightforward logic, so no [I do not feel like I need to remember a lot about it]." (P3.1)
(b)	"You could just like play around with the application for 2 to 5 minutes, and then it sticks in your head, it is easy to remember." (P3.6)
(c)	"I think I can just remember it without even thinking about it. [...] I connect it with a different idea, what this reminds me of is, like I told you, a match making system. [...] I use a similar approach, and it is just easy to remember." (P3.2)
(d)	"If I know what the tree is, the concept of a tree, I do not think I would need anything else to describe it. [...] Actually I do not think I would ever forget it, like it is impossible." (P3.7)
(e)	"Once you have seen it, that is kind of it I think. Once you have got it, then when you look at it again, you understand it." (P3.3)
(f)	"It is fairly simple, [the Explanation System] shows you what you need [to remember it]." (P3.5)

Table 6.6: Participants' quotes about their memorisation strategies for the Agglomerative Method.

With Group 2, all but participants P3.11 and P3.15 were able to describe the Projective Method without looking at its Explanation System (Table 6.7a). Given their low confidence in identifying the multidimensional nature of the data, we expected them to express difficulties in memorising the Projective Method. Instead, participants were able to describe components and behaviours in general terms, for example P3.13 in Table 6.7b. P3.12 attributed this to the visual aspect of the projective Explanation System, and commented that it would help for their long term memory as well (Table 6.7c). P3.14 and P3.16 explained that they would instead focus on the broad details and the actions' repetition to help with their memorisation task (Table 6.7d and 6.7e).

When asked to describe their memorisation strategies for the Projective Method, the participants of Group 2 proposed three alternatives. The first one consisted of using the visuality of the projective Explanation System, as P3.9 and P3.16 explained in Table 6.8a and 6.8b. Then, P3.10, P3.12, and P2.14 described that the Projective Method contained memorable broad details for them to confidently remember it (Table 6.8c and 6.8d). Finally, P3.11, P3.13, and P3.15 reckoned they

(a)	"Without looking at anything on the screen? [. . .] No." (P3.11)
(b)	"You choose [. . .] the row that has the most similar clustered groups, remove that row, and then you remove all the other rows until you have one left, and then using that one, you overlay it with an hexagonal grid, and then you kind of try and do a nearest neighbour kind of thing [. . .] I think, that is what I am assuming." (P3.13)
(c)	"[After a few days, I would remember] most of it I think, the end of it makes proper sense, it is like a cool interaction, and cool visuals so I think I would remember that." (P3.12)
(d)	"I would remember that the process is recursive, I would probably remember the process of elimination. Because they are quite big details." (P3.14)
(e)	"It is easy, it is built in a very structured way. I mean, it is always the same thing, it removes and so on. So it is not like unpredictable or something." (P3.16)

Table 6.7: Participants' quotes about their ability to memorise the Projective Method.

would need to fully understand the Projective Method first (Table 6.8e and 6.8f).

For both our Layout Methods, our participants communicated confidence in memorising the mapping process by using the visuality of an Explanation System.

When we specifically focus on the mapping processes, we find two properties that help memorisation. Firstly, there is the mapping process's understandability. While it was made clear by participants of Group 2 that the Projective Method requires them to work on understanding it, participants of Group 1 described the Agglomerative Method as simple enough to remember it almost immediately. We believe that this simplicity can be explained by the fact that the agglomerative mapping process uses an intuitive concept, a hierarchical tree. When not known already, this concept allows the participants to associate similar known notions with it.

Secondly, we found that mapping processes with generalisable steps, e.g. steps that can be grouped under one principle action, facilitated the participants' memorisation task. This strategy was predominant when participants experimented with the Projective Method, where they were able to summarise the mapping process in

(a)	"[I would remember] how the animation showed me, I would probably do that, but I am quite visual. [...] Memorising it that way, visually, is easier for me." (P3.9)
(b)	"Practising it would be good, and memorising it simply like trying to visualise it in my head, and just do the same thing as I was doing on the computer." (P3.16)
(c)	"I would probably generalise all the [assignment to grid actions], until it is only one stage, and then the removing [dimensions] stage, and then the final [Topic Map] I guess. [Interviewer: So you would group actions together?] Yes." (P3.12)
(d)	"I think process of elimination. If I have got that fact [...] that is enough prompt to remember the other broad details. [...] I think the process of elimination basically sums it up." (P3.14)
(e)	"If you have a good understanding of it, there is no need to memorise anything." (P3.11)
(f)	"The main thing is that you would just have to understand the process to remember [it]. [...] If it does not make sense in your head, you can not relate that to anything, and you just forget." (P3.13)

Table 6.8: Participants' quotes about their memorisation strategies for the Projective Method.

two processes: elimination and grid assignment.

6.4.4 Confidence of Presentation

Four of the eight participants of Group 1 stated they would present the agglomerative mapping process using its Explanation System in order to do so confidently (Table 6.9a and 6.9b). For P3.5, the nature of the similarity measure between topics could be of importance for their audience (Table 6.9c). Finally, according to P3.4, a presentation strategy using metaphors was deemed necessary, given the non-technical nature of the audience (Table 6.9d).

Participants of Group 2 expressed difficulties concerning the presentation task with the Projective Method (Table 6.10a to 6.10c). The visuality of the Explanation System however provided confidence, for example with P3.9 and P3.12 in Table 6.10d and 6.10e. Two presentation strategies emerged. For P3.11, the Explanation System

(a)	"If you were to explain it, like raw commentary at the same time, then I think they would understand it. [...] I think initially, it would be a little bit confusing, but then, as you go over it would be alright." (P3.3)
(b)	"It is definitely easier to show visually." (P3.5)
(c)	"If someone asked "how do you group by similarity", then I would not know. I do not know how you came up with the similarity." (P3.5)
(d)	"For a less technical audience, you could use metaphors [...] If someone needs clarification, I would go into more details if necessary. [...] Maybe I would not use tree, I would use bags or something "we put things in a bag that are similar." [...] Maybe people are not technical, but they are from some background, they have some concepts that are similar." (P3.4)

Table 6.9: Participants' quotes about the presentation of the Agglomerative Method.

could be simplified, by reducing the number of dimensions in the first place, and using a familiar concept (Table 6.10f). As for P3.14, generalising the process into key simple actions would be enough for the audience (Table 6.10g). Finally P3.16 reported that the concept of "lowest differentiation" would present a challenge for their audience (Table 6.10h).

As for the memorisation tasks, the visuality of the Explanation Systems had impact on the participants confidence in presenting the mapping processes in front of an audience.

When looking into presentation strategies, the comments made on both Layout Methods let us determine two mapping process characteristics that helped participants. With the Agglomerative Method, one participant in Group 1, P3.4, described their use of metaphors to make the mapping process accessible to a non-technical audience. In Group 2, P3.11 suggested the same principle of metaphor, this time applied to the data. We therefore found both the agglomerative and projective Layout Methods to be versatile enough and adaptable to different contexts, a characteristic that helped our participants to implement presentation strategies. The second characteristic is the generalisability of steps, as explained by P3.14, which we also identified in the memorisation task.

(a)	"I understand the process, but I am lost on the basic words to use, if that makes sense." (P3.9)
(b)	"If you know the algorithm, I do not see why you should not be able to do it. But I could not do it right now." (P3.11)
(c)	"I would not know how to describe it to be honest." (P3.12)
(d)	"The visual aspect of it [. . .] helps me. [. . .] The process I think is best explained alongside the animation." (P3.9)
(e)	"I think the visual was pretty clear. [. . .] I would probably struggle to explain it [if there is no visual]." (P3.12)
(f)	"With something small, probably three or four dimensions [. . .] it should be easier. [. . .] If you take [. . .] something that everybody has a grasp of, like [. . .] vegetables. So you can take the colour of the vegetable, the taste, the texture, [. . .] something that everybody is familiar with. [. . .] You could categorise them step by step, and they would be like "yes this makes sense", and the end result would make sense." (P3.11)
(g)	"I think I would try and describe it in the most abstract way possible." (P3.14)
(h)	"We are saying find lowest differentiation, this can still sound like black magic to someone, so yes, I would definitely introduce some concepts before." (P3.16)

Table 6.10: Participants' quotes about the presentation of the Projective Method.

For both of the Layout Methods, participants reported difficulties. In the Agglomerative Method case, these difficulties concerned the nature of both the topics and the similarity measure between topics. Such issues are however outside of the scope of this study, since we are focusing on the mapping processes mechanisms. With the Projective Method, participants of Group 2 described their difficulties in presenting mainly caused by their lack of understanding the concepts used in the mechanisms, or their ability to communicate them correctly. Given the presentation strategies identified, we believe that the projective mapping process is too intricate to allow the participants to overcome these difficulties.

(a)	"The mechanisms are good and simple." (P3.2)
(b)	"After following it through, and seeing it, and realising the links and stuff, it makes sense." (P3.3)
(c)	"You do not need technical knowledge to explain it, it just groups things by similarity. I do not think there is any technical aspects you need to go into with a non-technical person. " (P3.5)
(d)	"I would say it would be good, for a non-technical audience. Because, it is just clear, the logic is relatively easy to grasps." (P3.8)
(e)	"I think it might be easier [for a non-technical person], because, me as a programmer or machine learning person, I think I was misled at first. [. . .] It is not the difficulty of the program that made it harder for me to understand. [. . .] It is straightforward. That is my problem, I am trying to find what I do not understand, maybe I have understood it, maybe it is too easy, and I think that I miss something." (P3.7)

Table 6.11: Participants' quotes about the perceived difficulty with the Agglomerative Method.

6.4.5 Perceived Difficulty

The Agglomerative Method was reported to be simple and intuitive by six of the eight participants of Group 1, for example in Table 6.11a and 6.11b. And for five of them, this simplicity would fit the purpose of explaining the mapping process to an non-technical audience (Table 6.11c and 6.11d). In fact, P3.7 reported that it would be easier for users without technical background. With a background in programming they were actually misled, thinking the agglomerative mapping process was too obvious and that there was something they are not understanding (Table 6.11e).

Two participants in Group 2, P3.9 and P3.10, thought that the Projective Method was simple, especially given the visual Explanation System that accompanies it (Table 6.12a and 6.12b). The other six participants thought differently, for example P3.11 in Table 6.12c. P3.14 reported a lack of necessary background knowledge to interpret the projective mapping process confidently (Table 6.12d). Similarly, P3.11 and P3.16 did not think it would be fit for an audience with little

(a)	"It was quite self-explanatory once you have run through the all animation and everything. [...] I think it would be fine to be able to explain." (P3.9)
(b)	"Maybe visualising it helps more, maybe by describing it would take longer." (P3.10)
(c)	"I only understand the output, like it does the job, but I do not know how it did it." (P3.11)
(d)	"I do not really understand what is going on. [...] I do not really have the background information to know. [...] I think if I knew more about data mining, I would probably understand it." (P3.14)
(e)	"[A non-technical audience] would have a hard time just getting, understanding what more than 3 dimensions are. What does it mean that the data has 8 dimensions? There is no way they would grasp that concept." (P3.11)
(f)	"I would not say it is the easiest thing to get a good grasp of. And especially, again, for non-technical people." (P3.16)
(g)	"[I would] probably [need to practice] a good bit. But for someone who knows about this stuff, it probably would not be too bad." (P3.12)
(h)	"I just spend more time with it until I learn it. [...] I think it would take a little bit of time, like any system really, but it should be fine." (P3.15)

Table 6.12: Participants' quotes about the perceived difficulty with the Projective Method.

technical background (Table 6.12e and 6.12f). Finally, P3.12 and P3.15 expressed their need to practise more with the projective Explanation System in order to confidently interpret it (Table 6.12g and 6.12h).

In terms of perceived difficulty, the two Layout Method received divergent feedback.

The simplicity, in behaviour, of the Agglomerative Method, made it intuitive and independent of background knowledge, allowing the participants to confidently interpret it.

Although two participants of Group 2 found the Projective Method simple, the six other participants described a more challenging situation. For them, the Projective Method was difficult to interpret, and required background knowledge from them and their audience. Additionally, they reported needing more practise with

(a)	"In terms of grouping things by similarities, yes I think that is a really valid thing to do." (P3.1)
(b)	"Logic wise, I would not change everything, I think this is a really good approach, and it gets the point through." (P3.8)
(c)	"I would not come up with something easier to understand." (P3.8)
(d)	"[I would] group things, by how similar they are. I would probably do what I guess this does, group the most similar first. [...] I would say it is the most sensible option." (P3.5)
(e)	"I would group them together. [...] I think overall, in the end, I would try to build a tree, like here." (P3.7)
(f)	"I would have different clusters [...] and then within those clusters, start joining the similar topics, and then seeing where I can link from one cluster to another, based on that particular topic. That is what I would do." (P3.2)
(g)	"Some kind of clustering where similar thing kind of gravitate towards each other gradually, and then hopefully clusters emerge. [...] It would be just a ball of related concepts, another little ball of other related concepts, but they would not be immediately attach to each other." (P3.4)

Table 6.13: Participants' quotes about their canonical view of mapping process while experimenting with the Agglomerative Method.

the projective Explanation System to gain confidence using it.

6.4.6 Canonical View

All of the participants in Group 1 agreed with the logic used by the agglomerative mapping process, for example P3.1 and P3.8 in Table 6.13a and 6.13b. We discovered three patterns when asking the participants to describe how they would have generated Topic Maps. P3.8 stated they could not imagine an easier way to do so (Table 6.13c). P3.5 and P3.7 started describing mechanisms similar to the Agglomerative Method, before recognising that they were describing what they saw (Table 6.13d and 6.13e). The third pattern, explained by P3.2 and P3.4, makes use of clusters in different manners (Table 6.13f and 6.13g).

In Group 2, only three participants commented on the Projective Method's logic.

(a)	"Once the animation had played, it became, I thought, quite obvious." (P3.9)
(b)	"It looks reasonable to me." (P3.10)
(c)	"It reduces the dimensionality of the data. [. . .] That is a really technical thing to know, if I was not an engineering person, there is no way I would have understood it. [. . .] It is not obvious." (P3.11)
(d)	"I can not really think of a better way to do it. It seems like probably one of the best way to do it. [. . .] To decide what is the best solution, you would have to evaluate all solutions in some way." (P3.14)
(e)	"I would do it the same. [. . .] I am imagining it as some sort of assignment, I think I would go for the same approach." (P3.16)
(f)	"Start with one [topic], then put the next [. . .] most similar, and then you look at the next one, put the most similar, and as you get more you kind of know more or less where to put them because it becomes clearer." (P3.13)
(g)	"I would probably put [the topics] together. [. . .] Just to keep things together. I think this is better because [. . .] it makes it easier to see everything, and what is connected, and what is not." (P3.15)
(h)	"I guess the most obvious one is separate the science from the non-science. [. . .] Then I would just continue keeping on making subsets. [. . .] Then it is kind of like a tree I guess." (P3.11)

Table 6.14: Participants' quotes about their canonical view of mapping process while experimenting with the Projective Method.

For P3.9 and P3.10, it has a reasonable and obvious logic (Table 6.14a and 6.14b). P3.11, however, reported that the mechanisms used in the projective mapping process are too technical and not obvious (Table 6.14c). Three patterns emerged from asking the participants to describe their strategy for creating Topic Maps. P3.14 and P3.16 could not describe any approach other than the Projective Method, which they deemed best for this scenario (Table 6.14d and 6.14e). For P3.13 and P3.15, the ideal approach consisted of "putting things together", starting with the highest similarities (Table 6.14f and 6.14g). Finally, P3.11 described an approach based on divisive hierarchical clustering (Table 6.14h).

As expected from the experimental design, our participants' canonical view of mapping processes was biased in most cases towards the Layout Method they experimented with during the interview. This was especially true with the participants from Group 1, experimenting with the Agglomerative Method. With Group 2 however, we observed that when they do not rely on the Projective Method, the participants used mechanisms such as “clustering” and “aggregation by most similar first”, which are prevalent in the Agglomerative Method. This fact leads us to believe that the Agglomerative Method’s mechanisms, aggregation and clustering, are the ones that best correspond to the canonical view of mapping process. Using such mechanisms would allow the users to easily, rapidly, and confidently interpret the process presented to them.

6.4.7 Result Fitness

Participants of Group 1 reported being able to associate the agglomerative Explanation System with the resulting Topic Map (Table 6.15a and 6.15b). In P3.4’s and P3.7’s cases, it mostly inheres in the clusters presented by the Topic Map (Table 6.15c and 6.15d). When asked whether they could perceive the agglomerative mapping process by just looking at the Topic Map, two views emerged from the participants. P3.1 and P3.4, for example, described being able to partly discern the hierarchy used through the presence of clusters (Table 6.15e and 6.15f). But for P3.2 and P3.3, this was hardly manageable (Table 6.15g and 6.15h).

Apart from P3.11 (Table 6.16a), the participants of Group 2 reported being able to relate the projective Explanation System to the resulting Topic Map. For P3.15, this association happened as they interacted repeatedly with the Explanation System (Table 6.16b). With P3.12, P3.13, and P3.14, the last step of the projective mapping process, the assignment process, enabled this accordance (Table 6.16c to 6.16e). When asked about the correspondence from the Topic Map to the mapping process, five participants reported being unable to perceive any, for example P3.10 and P3.13 in Table 6.16f and 6.16g.

By asking our participants to reflect on the association between the mapping process and the Topic Map, and analysing their views, we uncovered two characteristics. The importance of clusters in the Agglomerative Method, and their presence

(a)	"Once you see what is going on, it is fairly easy to pick up that this is what is going to happen in the end." (P3.5)
(b)	"I would say, when two of those clusters formed I was able to predict what would be happening later." (P3.8)
(c)	"I would guess the [cluster] boundaries." (P3.4)
(d)	"I would know immediately that after this layer these three would be together." (P3.7)
(e)	"I can see how the different sections of the [Topic Map] represent [. . .] different levels of joining on the dendrogram." (P3.1)
(f)	"If I would have never seen the [Explanation System] and only have the [Topic Map], [. . .] I would kind of build a similar tree, up to a certain depth." (P3.4)
(g)	"If you look at the conceptual map itself, you can not really tell how they became linked." (P3.2)
(h)	"I can not convert that [Topic Map] to that [Explanation System] in my head. [. . .] It makes sense seeing it, but I could not really do it." (P3.3)

Table 6.15: Participants' quotes about the fitness between mapping process and Topic Map with the Agglomerative Method.

in the Topic Map, allowed the participants to better make this association. In the Projective Method, it was mainly achievable when the participants observed the assignment process. We believe this suggests that the presence of topics in multiple instances, during the dimensionality reduction process, made the association harder.

6.5 Discussion

This work presents contrasts between the Layout Methods, and in particular emphasised on the participants' confidence in interpreting and explaining these Layout Methods.

To our knowledge, no work as looked into the perception from users, with regards to their confidence of interpretation and explanation, of mapping processes, or visualisation processes in general. The study conducted here presents initial efforts towards establishing a methodology to investigate such aspects. We believe it

(a)	"I do not know how it came to this final map, like I do not see it. [...] I do not know what kind of steps it is taking." (P3.11)
(b)	"The more I used it, I could [foresee the result]." (P3.15)
(c)	"I did not get that it will build up to that [Topic Map]. [...] I only picked up when it was starting to move at the end there. [...] It sort of helps you to understand what is going on, to see like the last couple of stage maybe." (P3.12)
(d)	"[I could foresee the Topic Map] when the hexagons came up, here, before they started moving [for the assignment algorithm]." (P3.13)
(e)	"I could see after it selected the final arrangement, I think basically you slide it to the closest cell." (P3.14)
(f)	"I think it is hard to see the layout from [the Topic Map] to [the Explanation System]." (P3.10)
(g)	"[I: How much of the underlying process do you identify behind the topic map?] [...] Not much really. I mean not without actually clicking, just by purely looking at it then, not much." (P3.13)

Table 6.16: Participants' quotes about the fitness between mapping process and Topic Map with the Projective Method.

would be beneficial for the Human-Computer Interaction community to follow-up from this work, consolidate this methodology, and establish guidelines to study user confidence in algorithmic processes.

However, the main limitation of this study is its lack of grounding in actual task activities, mainly memorisation and presentation tasks, due to pragmatic constraints. As a result, our participants' statements regarding these tasks, despite the focus on their impression and confidence, remain hypothetical. This offers grounds for possible extension of Study 3.

6.6 Conclusion

This study investigated the impact of mapping processes' characteristics on user confidence. In particular we focus our attention on the process complexity and the user familiarity to isolate six research objectives (Section 6.1):

- the *Identification* of components and behaviours in the Layout Method;
- the *Confidence of memorisation* of the Layout Method;
- the *Confidence of presentation* of the Layout Method;
- the *Perceived difficulty* or the mapping process;
- the *Canonical view*, or instinctive conceptualisation of mapping processes;
- the *Result fitness* between the Layout Method and the Topic Map.

We present in Sections 6.2 and 6.3 our design and procedure to explore these objectives. We used both the agglomerative and projective Layout Methods to create a rich set of stimuli and contrast our results which we present in Section 6.4.

		Used in		Effect on
		Agglomerative Method	**Projective Method**	**User Confidence**
Components	Topics	●	●	✔
	Linkages	●		✔
	Clusters	●		✔
	Scatter plots		●	✘
	Scatter plot matrix		●	✘
	Grid		●	✔
Mechanisms	Aggregation	●		✔
	Dimensionality reduction		●	✘
	Grid assignment		●	✔

Table 6.17: Study 3's findings summary. In the *Used in* column we highlight the different uses of components and mechanisms in the agglomerative and projective Layout Methods (●). In the *Effect on User Confidence* column, we indicate whether these usages allowed the user to feel more confident (✔) or less confident (✘).

We summarise our findings in Table 6.17, were the ticks are determined based on our participants' statements. In the agglomerative Explanation System, the participants were confident in identifying and understanding the topics and linkages. Additionally, they made use of the emerging clusters to better associate the agglomerative mapping process to the Topic Map. With regard to the aggregation mechanism used in the Agglomerative Method, the participants easily and confidently understood it. They also instinctively used such mechanism, along with clustering, when asked to describe mapping processes.

With the projective Explanation System, participants were also able to confidently identify the topics, as well as the grid used at the end of the projective mapping process. Difficulties however arose, due to the multiplicity of the scatter plots and the character and purpose of the multidimensional scatter plot matrix. Similarly, the interpretation of the dimensionality reduction was challenging, while the grid assignment process was understood correctly and with confidence.

Finally, both Layout Methods made use of repeating steps, which the participants were able to group into few types of operations, a feature that allowed them to feel more confident in tasks such as memorisation and presentation.

We therefore draw the following recommendations for mapping processes:

- Implementing aggregation or clustering mechanisms, by putting most similar items together, will aid the user relate to the mapping process faster and with more confidence.
- Making use of few repetitive processes will facilitate the summarisation of the mapping process for the user, in turn allowing for a better and more confident interpretation, memorisation, and explanation of the mapping process.
- Presenting multiple competing views of the same data will cause confusion for the user's set of tasks, making it harder for them to perform such tasks with confidence.

Study 3 concludes our set of studies. In the next chapter, Chapter 7, we present the conclusion of this thesis.

Chapter 7

Conclusion

In this final chapter, we summarise our research and present our conclusions. Section 7.1 will first re-contextualise our motivation and goals. We then describe our methodology (Section 7.2) before outlining the contributions of this thesis (Section 7.3). We finally present possible future work in Section 7.4.

7.1 Motivation and Goal

This research originated from informal interviews of users interacting with automatically generated Topic Maps. While appreciating the engaging and informative nature of those, they expressed doubts when considering the use of such visualisations for high impact activities. The basis of such doubts lies in the users' lack of confidence in communicating those mapping methods, in particular their unbiased nature and integrity to the underlying data.

We therefore set as our main goal the identification and understanding of ways of improving the users' confidence in their ability to explain automated Topic Map layouts to themselves and to third parties.

In pursuit of this goal we found three research objectives:

1. To investigate the effects of data-driven Explanation System.
2. To investigate the effects of visual characteristics of Topic Map layouts.
3. To investigate the effects of algorithmic characteristics of Layout Methods.

7.2 Methodology

Examining the literature (Chapter 2), we identified two suitable processes to generate Topic Map layouts. Firstly, the Projective Method, follows a reductive approach, representative of the current state of the art in mapping techniques. Secondly, the Agglomerative Method, follows a constructive approach. We designed it to get a richer set of stimuli, and gather more meaningful insights from our participants.

We then created an algorithmic pipeline to generate Topic Maps. Chapter 3 presents in details the implementation of this pipeline including:

- our data collection process;
- the topic generation through topic modelling;
- the two mapping processes.

Following the structure of our research objectives, we split our work in three qualitative studies. For each of these studies, we presented participants with stimuli and a scenario in which we asked them to place themselves. We then conducted stimulated-recall semi-structured interviews.

Our first study, Study 1, aimed at contrasting participants' self-reported confidence between three conditions (Chapter 4). First with no explanation of the Topic Map layout, then with an explanation from one of the mapping processes, and finally with an explanation of the other mapping process. We developed these Explanation Systems in line with what has already been established by the literature (see Chapter 2) and designed them to be visual, interactive, and data-driven.

Amongst other contributions regarding data-driven Explanation Systems, which we detail in Section 7.3, the results of Study 1 results allowed us to discover layout and algorithm characteristics of interest to the participants and their confidence.

In Study 2, we presented participants with a set of ten Topic Maps (Chapter 5). These stimuli combined different number of clusters and levels of density, in turn producing varying visual characteristics across these Topic Maps. The interviews with the participants led us to discover which of these layout characteristics allowed for an improved confidence in explaining Topic Maps.

Finally, in Study 3, we set six research objectives and analysed the participants' response to these objectives regarding either the Agglomerative Method or the Projective Method (Chapter 6). These research objectives comprised of tasks for the explanation of mapping processes (identification, memorisation, and presentation), and properties affecting the cognitive load (perceived difficulty, canonical view of mapping process, and fitness between a mapping process and its result). Contrasting the participants' responses, we identified algorithmic characteristics to aid non-technical users understand Topic Maps' mapping processes with better confidence.

7.3 Contributions

Scope and Design

Beyond the results from our three studies, which we present in the following sections, this research presents contributions in its approach and in the systems it uses.

Firstly, there is the focus on user confidence, that is, the users' perception of their own ability as we define it in 2.2.1, to interpret and explain processes (primarily mapping processes). In addition, we also propose, throughout this thesis, a qualitative methodology to study user confidence (Sections 4.7 and 6.1).

Secondly, we detail in Section 3.3.2 a novel mapping process using hierarchical clustering at its core. By constructing a hierarchy of topics first, it then uses it to position topics in relation to each other. This allows the most similar topics to be put next to each other first, with the rest of the topics added gradually while minimising error from the similarity data. We later found that mechanism to correspond with participants' instinctive view of mapping processes (6.4.6).

Finally, we propose a general set of three requirements for Explanation Systems of visualisation processes: be *visual*, incorporate *interactivity*, and be *data-driven*. The results of our first study confirm the positive impact of these requirements on user confidence.

Effects of Data-Driven Explanation Systems

In Study 1, we found that incorporating Explanation Systems within Topic Map applications, greatly improved the participants' confidence.

Our participants found that, in particular, the data-driven property of these Explanation Systems increased their perception of the Topic Maps robustness, while helping their understanding of it, and improving their confidence in explaining it to other.

These advantages are accentuated by the interactivity of the Explanation Systems, as it allowed the participants to query individual items and pace the explanation to get more control over their understanding of the Layout Method.

Finally, we found eagerness in our participants to adopt and reuse this type of explanation mechanism.

Effects of Topic Map Layouts Characteristics

In Study 2, our participants highlighted three Topic Map layout characteristics that impacted their confidence in interpreting and explaining Topic Maps.

The first of these characteristics is the presence of clusters. Medium and small sized clusters give structure to the Topic Maps, easing the participants' interpretation and explanation tasks.

The second characteristic affecting participants' confidence is the level of density presented by Topic Maps. High density (fully connected) Topic Maps perceptually removed the structure enabled by clusters, and confused the participants by presenting competing narratives. Medium dense (semi-connected) Topic Maps let the participant perceive one narrative, and increased their confidence. Low density (disconnected) Topic Maps allowed for a better perception of clusters from the participant, while giving them the ability to construct narratives, overall improving their confidence in interpreting or presenting these Topic Maps.

The third characteristic is the set of landmarks within the Topic Map layout, including the size of labels and the shape of regions of the Topic Map. The presence of these landmarks increased the participants confidence by giving them cues for their interpretation, memorisation, and presentation tasks.

Effects of Mapping Processes Characteristics

In Study 3, we explored our participants responses towards the two mapping processes presented, and contrasted them to establish guidelines for interpretable mapping processes.

The participants interpreted the mechanisms of the agglomerative mapping process with ease and confidence, which was not the case with the projective mapping process. In addition, their canonical view of a mapping process reflected mechanisms such as aggregation and clustering, regardless of the mapping process they experimented with. Finally, the presence of clusters in the Agglomerative Method made the relation between the agglomerative mapping process and the result Topic Map easier, increasing their confidence of interpretation. As such we found that aggregation and clustering mechanisms core to mapping processes better suit users expectations, and ease their interpretation and explanation tasks.

In contrast, the multidimensional nature of the scatter-plot matrix used in the Projective Method confused the participants, as did the dimensionality reduction process. Despite being right in their interpretations on occasions, the participants reported having low confidence in it. It led us to conclude that presenting multiple competing views of the same information is a factor of confusion for non-technical users, and should therefore be avoided to aid confidence.

Finally, despite their difficulties with the Projective Method, the participants described the strategies they would employ to cope with it. The most mentioned, which was also noted with the Agglomerative Method, was the use of the repetitive processes. Being able to group actions under few classes simplified the mapping process for our participants, which in turn increased their interpretation and explanation confidence. We therefore recommend to make use of few distinct classes of actions to allow the participant to simplify the mapping process.

7.4 Discussion and Future Work

The research carried out in this thesis showed the importance for visualisation designers to consider the users' confidence in their ability to interpret and explain visualisation processes when conceiving visualisations. This thesis for example elaborated a mapping process for Topic Maps that relied on a constructive approach, and designed Explanation Systems that would allow users to witness mapping processes. Both resulted in our participants expressing higher confidence in explaining Topic Maps to others.

We therefore believe that considering constructive visualisation processes, and expanding Explanation System to other types of visualisations could bring beneficial result to the visualisation community.

The main limitation of our work however resides in the lack of grounding in real tasks. For pragmatic reasons, we were only able to discussed with our participants of hypothetical scenarios. Although our focus was on the participants' feelings and states of mind, being able to put them in real situations would have give us more qualitative results. Future work should therefore contrast the theoretical findings of this thesis with practical investigations.

We also think that future work should expand on the scope of this thesis. For example, we believe it would be useful to contrast user confidence between regular and irregular layouts, or understand the relationship (if any) between user confidence and cognitive load.

In a broader context, we aspire for this work to help establish a research area adressing user confidence in explainable systems. We have engaged in such work with a breakdown and classification of confidence issues in explanation systems [94].

We also believe that this work can be extended to further applications and domains, such as Machine Learning (ML), Artificial Intelligence (AI), Human-Robot Interaction (HRI) where a better understanding of user confidence, and the standardisation of Explanation Systems would be beneficial, if not necessary.

Appendices

Appendix A

Hexagonal Grids

The following notes are excerpts of *Red Blob Games*'s guide on hexagonal grids [89].

Size and Spacing

Given the size s of an hexagon (from center to corner), the width w of the hexagon is $\sqrt{3} \times s$, and its height h is $2 \times s$.

In a hexagonal grid with Cartesian coordinate system, the horizontal spacing between two neighbouring hexagons is w, or $\sqrt{3} \times s$. The vertical spacing is $h \times \frac{3}{4}$, or $\frac{3}{2} \times s$. Each row is displaced by $\frac{w}{2}$ or $\frac{\sqrt{3}}{2} \times s$.

Coordinate Systems

A direct way to represent the coordinates of hexagons is in a Cartesian system, with two coordinates (x, y). This system should be used when rendering hexagons on a screen (a Cartesian pixel space).

A more abstract alternative to this system is to consider a Cartesian system, with three dimensions (x, y, z), given that hexagons can be seen as sections of cubes. The cubic coordinate system is illustrated in Figure A.2.

Although the cubic system allows for easy transformation and distance measures, it requires to be changed into a two-dimensional Cartesian system, in order to display

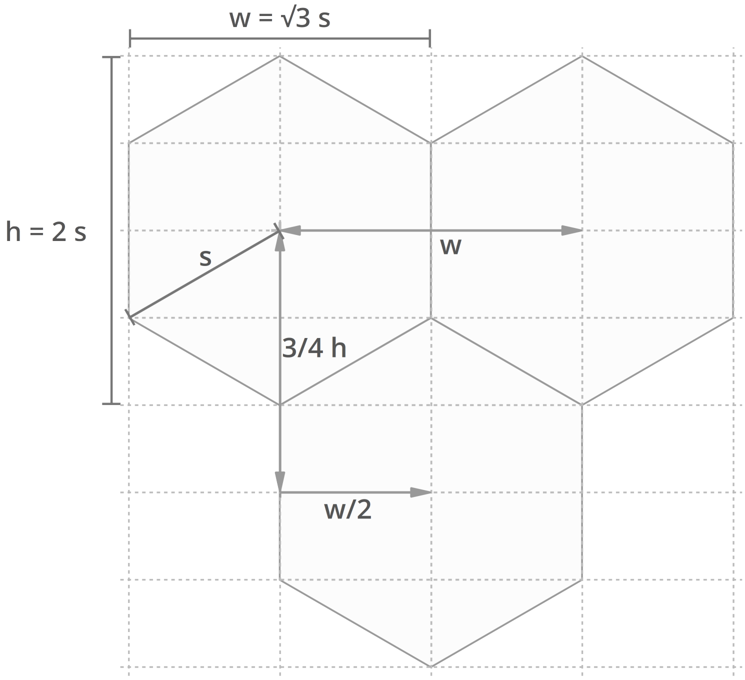


Figure A.1: Size and spacing of hexagons in a grid.

hexagons on a screen. As such the following operations are used:

$$x = (x_{cubic} - y_{cubic}) \times \frac{2}{\sqrt{3}}$$
$$y = z_{cubic} \times \frac{3}{2}$$

Distances and Transformation

The following apply in the cubic coordinate system.

The Euclidean distance between two hexagons a and b can be calculated with the formula: $dist_{a,b} = max(abs(x_a - x_b), abs(y_a - y_b), abs(z_a - z_b))$.

Rotating a hexagon 60 degrees clockwise, with the origin as center of rotation, is done as follow: $(x', y', z') = (-z, -x, -y)$.

Translating a hexagon by a vector (a, b, c) is done as follow: $(x', y', z') = (x + a, y + b, z + c)$.

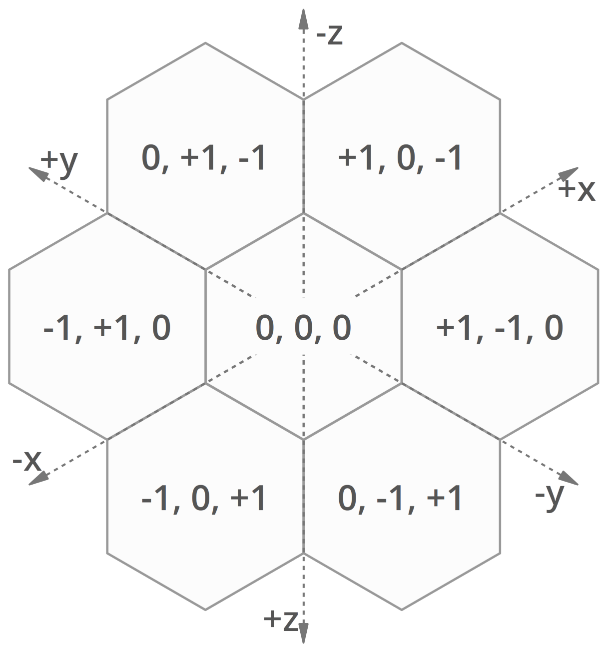


Figure A.2: Diagram of the cubic coordinate system for hexagonal grids.

Appendix B

Consent Form

Study Participation Consent Form

HERIOT WATT UNIVERSITY

Thank you for agreeing to take part in our research. This work is being carried out as part of a research funded by Heriot-Watt University.

Today, I will ask you to take part in a study, where you will be presented with an interactive application and a scenario to conduct an interview. Your task is to analyse, discuss and reflect on the application, considering the scenario, through a series of questions. Make sure to express your thoughts as much as possible. The interview will be recorded for transcribing purpose only. All video and audio files will be deleted.

You will be rewarded a £10 Amazon voucher for taking part in this experiment.

We will store the information confidentially, anonymously and unlinked to any personal details. All data will be collected and stored in accordance with the Data Protection Act 1998. You have the right to withdraw at any time without giving a reason.

Participant's Name ____

May we keep an anonymous copy of the demographic information you provide?

☐ Yes ☐ No

May we record (audio and/or video) your responses during the study for transcription purposes ? (The recordings will be deleted after the transcription has been completed)

☐ Yes ☐ No

May we keep an anonymous copy of the interview transcript ?

☐ Yes ☐ No

May we use excerpts of your interview transcript and demographic information in the future, for conferences, publications or presentations? (We will not report anything identifiable.)

☐ Yes ☐ No

I have been fully informed as to what this study will entail and am aware of my right to withdraw at any time. I hereby fully and freely consent to participation in the study, which has been fully explained to me.

Signed ____

Date ____

Figure B.1: Example consent form presented to and signed by participants. The second paragraph would change depending on the study task.

Appendix C

Study 1 - Mapping Processes Numerical Comparison

The mean squared error of each Topic Map consists of the average squared difference between the Euclidean distance of every pair of items in the Topic Map (Equation (3.11)) and the original distance measure in the dissimilarity matrix D.

Table C.1 present the descriptive statistics of these measures. Table C.2 presents the mean squared error values for each of the 250 Topic Maps used in this analysis. The first column indicates the number of topics in the Topic Map (xt) and the number of document used to generate the distance matrix (yd).

	Agglomerative	**Projection**
Average	0.213435	0.209385
Variance	0.000779	0.000717
Standard deviation	0.027906	0.026774
Standard error	0.002496	0.002395

Table C.1: Mean squared error descriptive statistics of 250 Topic Maps.

Methods	Agglomerative					Projection				
Subset	1	2	3	4	5	1	2	3	4	5
10t 100d	.1779	.1282	.1227	.1569	.1504	.1564	.1231	.1654	.1637	.1493
10t 500d	.1832	.1810	.1561	.1544	.1527	.1550	.2241	.1738	.2040	.1574
10t 1000d	.1746	.1789	.2283	.2256	.2247	.1916	.2004	.2791	.1617	.1830
10t 2000d	.1698	.1885	.1889	.1890	.1720	.2239	.1881	.2490	.1779	.1819
10t 3000d	.1908	.1913	.1815	.1870	.1777	.2286	.2040	.1823	.2206	.2187
20t 100d	.2342	.1920	.1981	.1957	.2100	.1884	.2060	.1982	.1908	.1966
20t 500d	.1994	.2022	.1620	.1982	.2140	.2089	.1656	.1919	.1865	.2271
20t 1000d	.2221	.1949	.2065	.1903	.1975	.1763	.2074	.1735	.2192	.2154
20t 2000d	.2365	.2279	.2537	.2393	.2248	.1952	.2163	.2193	.2171	.2261
20t 3000d	.1943	.2417	.2114	.2088	.2448	.2220	.2093	.2168	.2562	.2199
30t 100d	.2389	.2614	.2452	.2294	.2397	.2059	.2290	.2445	.2516	.2299
30t 500d	.2242	.2272	.2272	.2324	.1963	.2214	.2240	.2078	.1895	.2207
30t 1000d	.2064	.2252	.2006	.2102	.2315	.1904	.1969	.1749	.2071	.2130
30t 2000d	.2348	.1883	.2228	.2179	.2576	.2255	.1890	.1995	.1877	.2073
30t 3000d	.2144	.2342	.2393	.2108	.2320	.1926	.2228	.1996	.2320	.1985
40t 100d	.2467	.2579	.2623	.2290	.2386	.2483	.2743	.2530	.2338	.2174
40t 500d	.2228	.2151	.1895	.2099	.2321	.2237	.1754	.2211	.2106	.2338
40t 1000d	.2024	.2068	.2200	.2168	.2220	.2209	.1826	.2208	.2036	.2098
40t 2000d	.2182	.2154	.2135	.2421	.2184	.1947	.1944	.2163	.2059	.2000
40t 3000d	.2157	.2161	.2100	.2102	.2031	.2380	.1972	.2305	.2136	.2030
50t 100d	.2732	.2520	.2465	.2608	.2588	.2349	.2789	.2597	.2702	.2521
50t 500d	.2140	.2190	.2635	.2298	.2383	.2336	.1941	.2382	.2090	.2024
50t 1000d	.2284	.2306	.2369	.2206	.2060	.2296	.1948	.2280	.2034	.2247
50t 2000d	.1976	.2128	.2225	.2432	.2313	.1962	.1992	.2053	.2320	.2015
50t 3000d	.2072	.2080	.2319	.2101	.2210	.2151	.2222	.2056	.2438	.2020

Table C.2: Mean squared error of 250 Topic Maps generated using both mapping processes. The first column indicates the number of topics in the Topic Map (xt) and the number of document used to generate the distance matrix (yd).

Appendix D

Study 1 - Participants

Participants	*P1.1*	*P1.2*	*P1.3*	*P1.4*	*P1.5*	*P1.6*	*P1.7*	*P1.8*	*P1.9*	*P1.10*
Age*	25	33	21	26	38	30	23	22	33	20
Occupation*	PhD	RA	UG	PG	PhD	PhD	PhD	PG	RA	UG
Static visualisations (Frequency)	5	2	4	3	4	3	4	5	2	3
Dynamic visualisations (Frequency)	3	0	2	2	4	3	3	6	2	4
Creating visualisations (Frequency)	6	3	4	3	3	5	4	3	2	2

Table D.1: Background information collected from the participants of Study 1. * indicates optional questions.

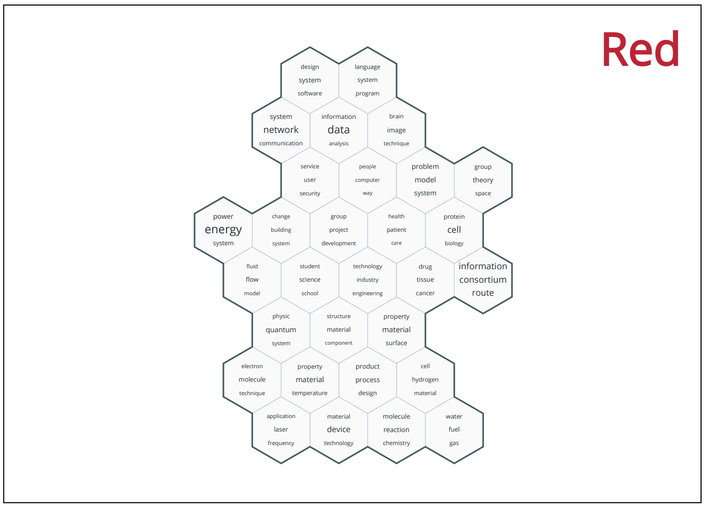
Table D.1 presents the background information gathered from the participants of Study 1 (P1.1 to P1.10). The questions marked with an * were optional, and the participants were simply asked to detail these information as they wished. The following occupations were recorded: *Undergraduate Student* (UG), *Postgraduate student* (PG), *Ph.D. student* (PhD), and *Research Associate* (RA).

The frequency questions were mandatory and used a 7-points Likert scale answer model: *Never* (0), *Rarely* (1), *Occasionally* (2), *Sometimes* (3), *Frequently* (4), *Usually* (5), and *Every Time* (6). These questions were formulated as follow:

- How often do you use static data visualisations (Charts, PowerPoint, Excel, infographics, etc.)?
- How often do you use dynamic data visualisations (interactive web applications, Google Charts, Tableau, interactive news infographics, etc.)?
- How often do you create visualisation from data (MATLAB, R, Python, PowerPoint, Excel, etc.)?

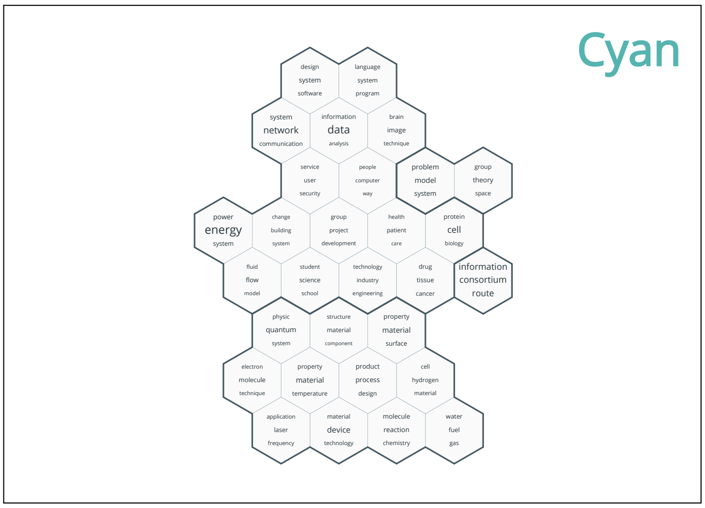
Appendix E

Study 2 - Stimuli

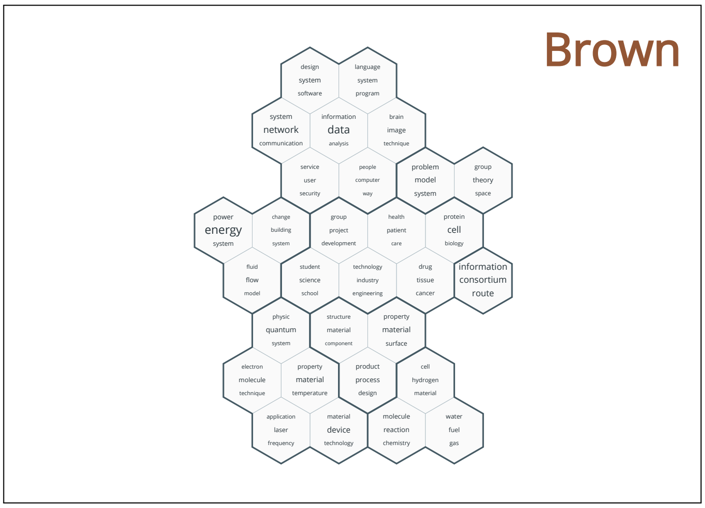


(a) $c = 1$, $\iota = 0.0$

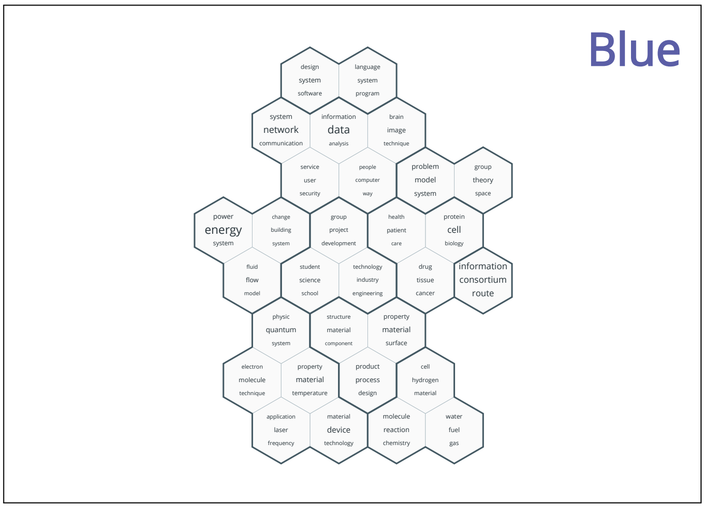
Figure E.1: Topic Map stimuli presented to participants in Study 2. These stimuli are designed to display a range of density (controlled by ι) and number of cluster (controlled by c) in their layouts. Each Topic Map was randomly assigned a color to aid identification during the interviews with the participants.



(b) $c = 4,\ \iota = 0.0$

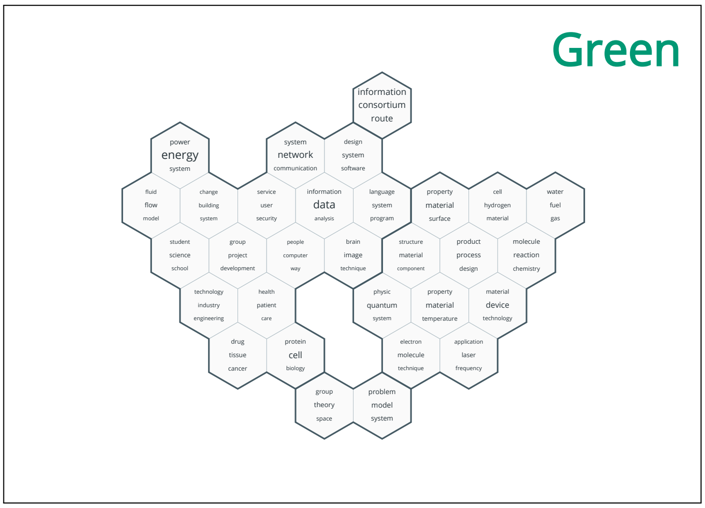


(c) $c = 8,\ \iota = 0.0$

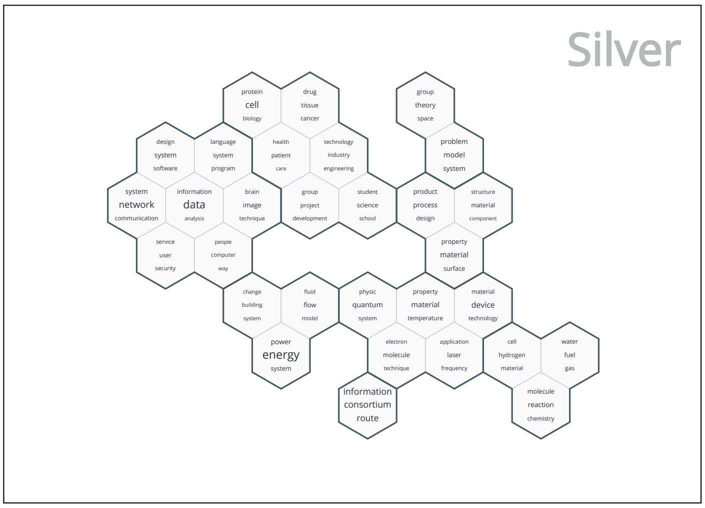


(d) $c = 10,\ \iota = 0.0$

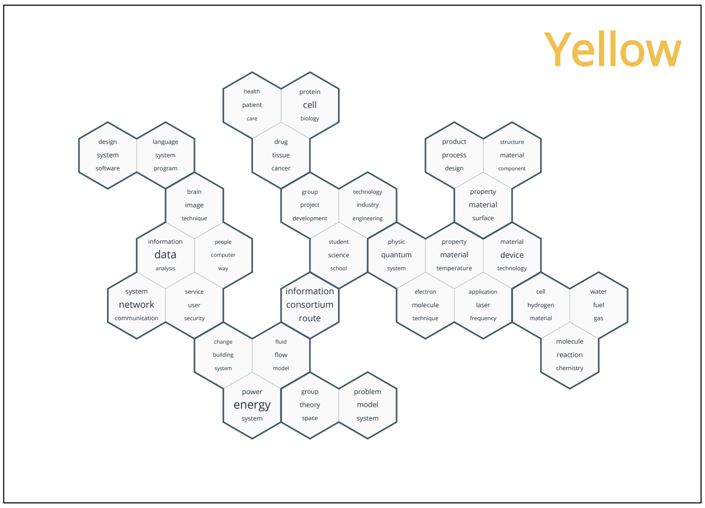
Figure E.1 (continued)**:** Topic Maps presented to participants in Study 2.



(e) $c = 4$, $\iota = 0.5$

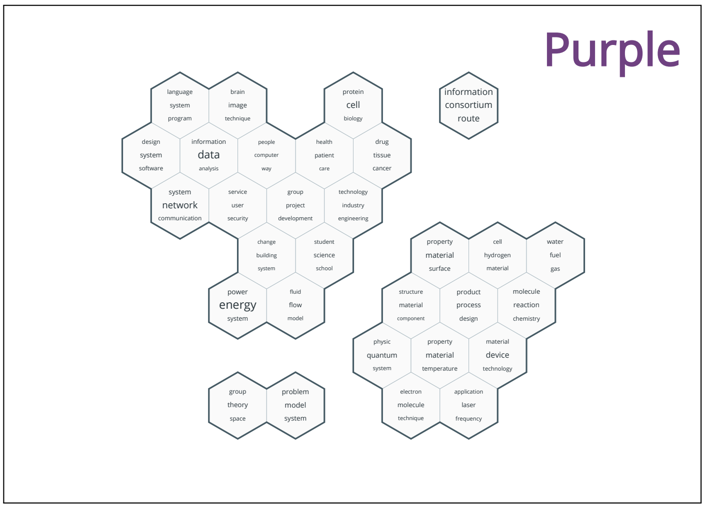


(f) $c = 8$, $\iota = 0.5$

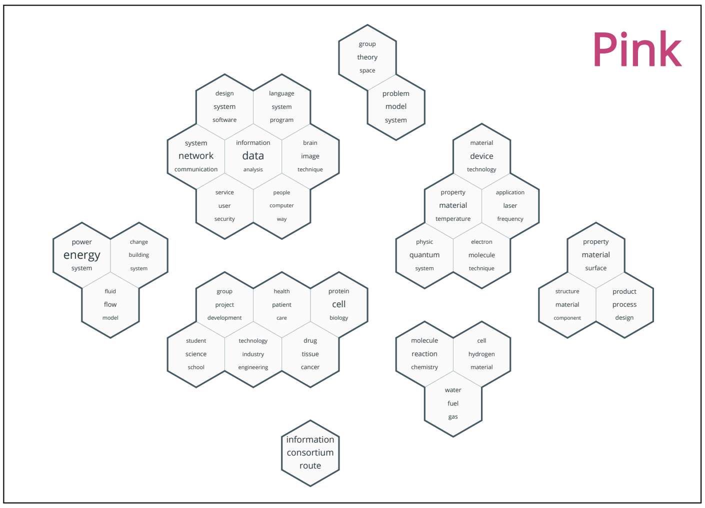


(g) $c = 10$, $\iota = 0.5$

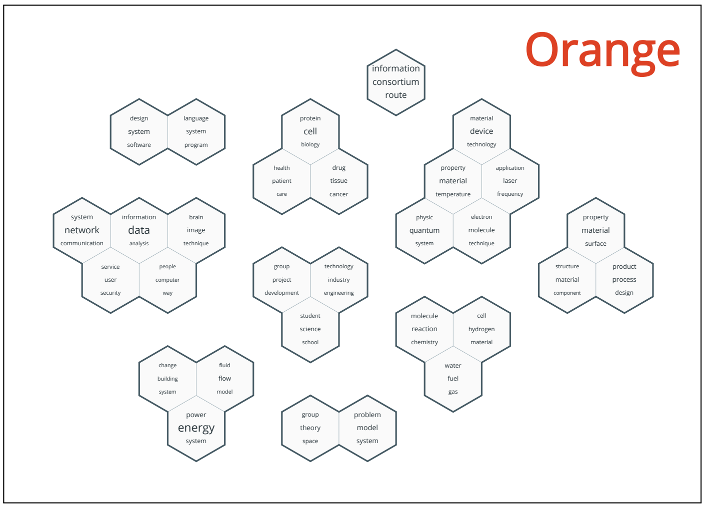
Figure E.1 (continued)**:** Topic Maps presented to participants in Study 2.



(h) $c = 4,\ \iota = 1.0$



(i) $c = 8,\ \iota = 1.0$



(j) $c = 10,\ \iota = 1.0$

Figure E.1 (continued)**:** Topic Maps presented to participants in Study 2.

Appendix F

Study 2 - Participants

Participants	*P2.1*	*P2.2*	*P2.3*	*P2.4*	*P2.5*	*P2.6*	*P2.7*	*P2.8*	*P2.9*	*P2.10*	*P2.11*	*P2.12*
Age*	46	21	29	25	28	-	33	26	20	26	26	27
Occupation*	RA	UG	PhD	PhD	PhD	-	UG	PG	UG	PhD	PhD	PhD
Static visualisations (Frequency)	2	2	2	3	4	4	2	4	3	1	4	4
Dynamic visualisations (Frequency)	2	1	1	0	3	4	4	4	2	0	2	4
Creating visualisations (Familiarity)	1	4	1	2	2	2	2	3	1	2	2	0
Data Mining (Familiarity)	3	4	2	1	2	3	1	1	1	0	0	4
Presentation (Familiarity)	3	3	3	4	3	3	2	4	1	3	3	1

Table F.1: Background information collected from the participants of Study 2. * indicates optional questions.

Table F.1 presents the background information gathered from the participants of Study 2 (P2.1 to P2.12). The questions marked with an * were optional, and the participants were simply asked to detail these information as they wished. The following occupations were recorded: *Undergraduate Student* (UG), *Postgraduate* *student* (PG), *Ph.D. student* (PhD), and *Research Associate* (RA).

The frequency and familiarity questions were mandatory and used a 5-points Likert scale answer model:

- Frequency: *Never* (0), *Almost never* (1), *Occasionally* (2), *Moderately* (3), and *Frequently* (4).
- Familiarity: *Not at all* (0), *Slightly* (1), *Somewhat* (2), *Moderately* (3), and *Extremely* (4).

The questions were formulated as follow:

- How often do you use static data visualisations (Charts, PowerPoint, Excel, infographics, etc.)?
- How often do you use dynamic data visualisations (interactive web applications, Google Charts, Tableau, interactive news infographics, etc.)?
- How familiar are you with the process of creation of data visualisation?
- How familiar are you with data mining techniques?
- How familiar are you with presenting results to an audience?

Appendix G

Study 2 - ANOVA of Stimuli Mentions Counts

The following tables present the results from the two-way repeated measures analysis of variance (ANOVA) we carried out on the stimuli mentions counts in the interviews from Study 2. Table 5.1 shows the full counts of stimuli mentions.

	Cy	**Br**	**Bl**	**Gr**	**Si**	**Ye**	**Pu**	**Pi**	**Or**
c	4	8	10	4	8	10	4	8	10
ι	0.0	0.0	0.0	0.5	0.5	0.5	1.0	1.0	1.0
Mean	3.00	3.92	2.92	6.50	7.92	16.97	4.42	13.75	14.17
Std. Dev.	2.828	2.778	2.937	5.584	6.201	7.395	4.582	8.237	9.331
N	12	12	12	12	12	12	12	12	12

Table G.1: Descriptive statistics of stimuli mentions counts. For brevity, we abbreviated the color codes to their first two letters.

	Mauchly's W	**Approx.** χ^2	**df**	**Sig.**
Clusters	0.648	4.342	2	0.114
Density	0.740	3.015	2	0.221
Clusters * Density	0.360	9.613	9	0.390

Table G.2: Mauchly's test of sphericity on stimuli mentions counts.

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Clusters	1279.167	2	639.583	16.990	0.000
Err(Clusters)	828.167	22	37.644		
Density	794.889	2	397.444	10.666	0.001
Err(Density)	819.778	22	37.263		
Clusters * Density	669.611	4	167.403	6.102	0.001
Err(Clusters * Density)	1207.056	44	27.433		

Table G.3: Within-subjects effects of the the stimuli mentions counts, with sphericity assumed (see Table G.2). These tests show a statistical difference of means for the number of clusters, the level of density, and the interaction between these two variables.

Clusters	Mean	Std. Err.
4	3.278	0.676
8	10.361	1.401
10	10.778	1.306

Table G.4: Estimates of the number of clusters means on the stimuli mentions counts.

(I) Clusters	(J) Clusters	Mean Difference (I-J)	Std. Err.	Sig.
4	**8**	-7.083	1.368	0.001
	10	-7.500	1.070	0.000
8	**4**	7.083	1.368	0.001
	10	-0.417	1.805	1.000
10	**4**	7500	1.070	0.000
	8	0.417	1.805	1.000

Table G.5: Pairwise comparisons of the number of clusters on the stimuli mentions counts.

Density	Mean	Std. Err.
0.0	4.639	0.993
0.5	8.528	1.095
1.0	11.250	1.386

Table G.6: Estimates of the level of density means on the stimuli mentions counts.

(I) Density	(J) Density	Mean Difference (I-J)	Std. Err.	Sig.
0.0	**0.5**	-3.889	1.459	0.066
	1.0	-6.611	1.062	0.000
0.5	**0.0**	3.889	1.459	0.066
	1.0	-2.722	1.719	0.425
1.0	**0.0**	6.611	1.062	0.000
	0.5	2.722	1.719	0.425

Table G.7: Pairwise comparisons of the level of density on the stimuli mentions counts.

Appendix H

Study 3 - Participants

Participants	P3.1	P3.2	P3.3	P3.4	P3.5	P3.6	P3.7	P3.8
Age*	27	22	21	33	23	20	22	26
Occupation*	PhD	PG	UG	RA	PG	UG	PhD	PhD
Static visualisations (Frequency)	4	3	3	4	3	3	2	3
Dynamic visualisations (Frequency)	1	3	1	4	3	4	1	2
Creating visualisations (Familiarity)	3	3	3	3	3	2	2	3
Data Mining (Familiarity)	4	2	1	3	3	1	2	3
Presentation (Familiarity)	3	4	3	3	3	2	1	4

Table H.1: Background information collected from the participants of Study 3. These participants were shown agglomerative Explanation Systems. * indicates optional questions.

Tables H.1 and H.2 present the background information gathered from the participants of Study 3 (P3.1 to P3.16). The questions marked with an * were optional, and the participants were simply asked to detail these information as they wished. The following occupations were recorded: *Undergraduate Student* (UG), *Postgrad-*

Participants	P3.9	P3.10	P3.11	P3.12	P3.13	P3.14	P3.15	P3.16
Age*	26	34	22	22	24	29	36	24
Occupation*	PhD	L	UG	UG	PG	PG	UG	UG
Static visualisations (Frequency)	2	2	2	2	2	1	3	1
Dynamic visualisations (Frequency)	4	4	4	4	2	4	3	1
Creating visualisations (Familiarity)	2	2	3	3	4	1	3	1
Data Mining (Familiarity)	2	2	2	0	3	0	2	2
Presentation (Familiarity)	2	3	3	2	3	1	2	3

Table H.2: Background information collected from the participants of Study 3. These participants were shown projective Explanation Systems. * indicates optional questions.

uate student (PG), *Ph.D. student* (PhD), *Research Associate* (RA), and *Lecturer* (L).

The frequency and familiarity questions were mandatory and used a 5-points Likert scale answer model:

- Frequency: *Never* (0), *Almost never* (1), *Occasionally* (2), *Moderately* (3), and *Frequently* (4).
- Familiarity: *Not at all* (0), *Slightly* (1), *Somewhat* (2), *Moderately* (3), and *Extremely* (4).

The questions were formulated as follow:

- How often do you use static data visualisations (Charts, PowerPoint, Excel, infographics, etc.)?
- How often do you use dynamic data visualisations (interactive web applica-

tions, Google Charts, Tableau, interactive news infographics, etc.)?

- How familiar are you with the process of creation of data visualisation?
- How familiar are you with data mining techniques?
- How familiar are you with presenting results to an audience?

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